The Dissertation Committee for Sudeshna Sen certifies that this is the approved version of the following dissertation:

A Joint Multiple Discrete Continuous Extreme Value (MDCEV) Model and Multinomial Logit Model (MNL) for Examining Vehicle Type/Vintage, Make/Model and Usage Decisions of the Household

Committee:

____
Chandra R. Bhat, Supervisor

____
Randy B. Machemehl

____
S. Travis Waller

____
Stephen Donald

____
Chandler Stolp

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by

Sudeshna Sen, B.Arch., M.U.P.P.

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Dedication

To my mother, Shukla Sen and my father, Sujoy Sen

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A Joint Multiple Discrete Continuous Extreme Value (MDCEV) Model and Multinomial Logit Model (MNL) for Examining Vehicle Type/Vintage, Make/Model and Usage Decisions of the Household

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Sudeshna Sen, Ph.D.
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Supervisor: Chandra R. Bhat

In this dissertation, we seek to contribute to the area of automobile demand modeling by developing a comprehensive econometric model to examine several dimensions of household vehicle holdings and usage decisions. In particular, we model number of vehicles owned as well as the following attributes for each of the vehicles owned: (1) vehicle body type, (2) vehicle age (i.e., vintage), (3) vehicle make and model, and (4) vehicle usage. We develop a comprehensive conceptual framework for modeling the choice situation of households characterized by the simultaneous choice of multiple vehicle types/vintages and usage decisions as well as the choice of a single make and model within each vehicle type/vintage chosen. We translate this conceptual framework into a utility-theoretic formulation to analyze the many dimensions of vehicle holdings and use. Specifically, we formulate a nested model structure that includes a multiple discrete-continuous extreme value (MDCEV) component to analyze the choice of vehicle type/vintage and usage in the upper level and a multinomial logit (MNL) component to analyze the choice of vehicle make/model in the lower nest. The model is estimated using data from the 2000 San Francisco Bay Area Travel Survey.

The model results indicate the important effects of household demographics, household location characteristics, built environment attributes, household head characteristics, and vehicle attributes on household vehicle holdings and use. Finally, the model developed in the dissertation is applied to predict the impact of land use and fuel cost changes on vehicle holdings and usage of the households. Such predictions can inform the design of proactive land-use, economic, and transportation policies to influence household vehicle holdings and usage in a way that reduces the negative impacts of automobile dependency such as traffic congestion, fuel consumption and air pollution.

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Chapter 1. Introduction

Motorized personal-use vehicles or automobiles play a significant role in the day-to-day lives of the American population. For instance, the 2001 National Household Transportation Survey (NHTS) data shows that automobiles dominate urban travel in the United States among every segment of the population, including poor, minorities and the elderly (Pucher and Renne, 2003). The dominance of the automobiles as a means of travel may be attributed, among other things, to the greater level of comfort, convenience and reliability provided by autos (relative to other modes) for most travel needs. The mobility and accessibility benefits associated with automobiles have led to an increasing dependence on automobiles as indicated by the increasing vehicle holdings and usage of the households. This chapter gives a brief background on automobile dependency, and discusses its wide-ranging impacts (section 1.1). Next, the importance of examining vehicle holdings and usage of the household as a measure of automobile dependency is discussed (section 1.2). Finally the overall objectives of this research are presented (section 1.3).

1.1 Automobile Dependency

Automobile dependency has been defined as "high levels of per capita automobile travel, automobile-oriented land-use patterns and reduced transport alternatives" (Litman, 2002; Newman and Kenworthy, 1998). The dependency on automobiles can be explained by a cycle of events: The increasing ownership and usage of personal-use vehicles by households is proliferated by automobile-oriented transportation policies, and reduced and unattractive non-automobile travel options. This affects the land-use patterns, leading to suburbanization of urban neighborhoods with auto-oriented land-use planning. The reduction in land-use accessibility due to suburbanization increases the dependence on automobiles and escalates the vehicle ownership and usage further (VTPI, 2004). The cycle of events clearly indicates the causal relationship between automobile dependency and vehicle ownership and usage. Furthermore, the dependence of the households on automobiles varies depending upon the socio-demographic characteristics of the household and has wide-ranging impacts not only at the household level but also at the community and regional level (as discussed in detail below).

1.1.1 Impacts of Automobile Dependency

Automobile dependency, on the positive side, satisfies the mobility and accessibility needs of the household, adding to their comfort and convenience. However, on the negative side, it significantly impacts the transportation expenses of the household. At a community level, automobile dependency can cause social and economic stratification and discrimination between different segments of the population. At a regional level, automobile dependency has wide-ranging impacts on traffic congestion, environment, health, economic development, infrastructure, land-use and energy consumption. The vast range of impacts caused by automobile dependency are discussed in detail in the following sections at three levels: household level, community level and regional level.

1.1.1.1 Impacts of Automobile Dependency at a Household Level

(1) Mobility and Accessibility

The comfort, convenience and reliability associated with automobiles as compared to other transportation alternatives have made it a dominant mode of transportation. Specifically, the increasing reliance on automobiles for urban travel has resulted in the decline in public transit and walking (Pucher and Renne, 2003). For instance, 2001 NHTS data indicates that the share of daily, local travel by autos has increased from 81.8% of trips in 1969 to 86.4% in 2001, while the share of public transit has declined from 3.2% to 1.6% over the same periods (Pucher and Renne, 2003).

Besides meeting the mobility needs of the people (VTPI, 2004), automobiles improve accessibility *i.e.* ease of reaching activities (Bhat *et al.*, 2000), enabling individuals to participate in more number of activities. For instance, NHTS data shows that autos served 92.1% of all the work trips, 91.5% of shopping trips, 84.1% of the social/recreational trips and 72.9% of the school and church trips, in 2001 (Pucher and Renne, 2003). All these benefits increase the dependence of households on automobiles.

(2) Costs to the Consumer

The increasing dependence of households on automobiles, as is apparent from their increasing vehicle ownership and use, leads to an increase in transportation expenses. For instance, the Consumer Expenditure Survey (CES) data shows that the transportation costs of the household increased by 2.9% from 2000 to 2001 and 1.7% from 2001 to 2002 (CES, 2004). Furthermore, the 2002 CES data indicates that 19.1% of the annual household expenditures is attributed to transportation (as compared to 18.5% in year 1995), out of which 47% is on vehicle purchases, 16% on fuel, 32% on other vehicle-related expenses (primarily, maintenance and repairs, vehicle finance charges, rentals and leases) and 5% on public transportation-related expenses. It is interesting to note that the expenses related to vehicle ownership and usage account for 95% of the total transportation expenses of a household.

As expected, the transportation expenses associated with vehicle ownership and use is financially burdensome for low-income households (income less than $20,000). The CES data indicates that the transportation expenses for low-income households account for almost 27% of their annual income. Besides the transportation expenses, consumers also have to pay parking and toll costs, which further increase the total costs incurred by the consumer for owning and using a vehicle.

1.1.1.2 Impacts of Automobile Dependency at a Community Level

(1) Social Impacts

Automobile dependency results in heavy vehicular traffic, which can reduce the social interaction opportunities between people, particularly the spontaneous exchange between residents (Litman, 2002; Engwicht, 1993; Untermann and Mouden, 1989). For instance, Carlson *et al.* (1995) indicated that automobile based development "magnifies the polarization of the society by increasing the geographical and time barriers between people with different incomes, and by making it more difficult for those who don't own cars to participate in life outside their communities. Additionally, automobile dependency encourages social stratification, resulting in people with similar income and lifestyle spending most of their lives in a common social environment (Litman, 2002).

(2) Equity Impacts

Equity as defined by Litman (2002) can be classified into (1) Horizontal Equity which requires that people with similar resources be treated alike and (2) Vertical Equity which requires that people with different income status be treated differentially (with greater benefits to people with lower income than higher income). Automobile dependency results in violation of both horizontal and vertical equity (with respect to income). For instance, the dependence on automobiles increases the external costs *i.e.* costs imposed by somebody other than the user (for example, infrastructure costs, financial subsidies such as free parking and indirect costs of externalities such as pollution), impacting both the drivers and non-drivers alike. Thus, the non-drivers subsidize the people who drive, resulting in the violation of horizontal equity (Litman, 2002). Further, automobile dependency makes the travel expenses (such as road tax and parking subsidies) more burdensome for lower income households compared to higher income households or gives more travel advantages to motorists over transportation-disadvantaged and physically challenged people, thereby violating vertical equity (Litman, 2005; Litman, 2002).

1.1.1.3 Impacts of Automobile Dependency at a Regional Level

(1) Traffic Congestion

Automobile dependency directly impacts household vehicle ownership and usage. Specifically, increasing dependence on automobiles leads to an increase in the number of vehicles using the roadway, thereby leading to the inevitable problem of traffic congestion (Litman, 2002; Schrank and Lomax, 2005). It is interesting to note that while the number of vehicle miles traveled has increased 74 percent since 1982, the road lane mileage has increased by only 6 percent (Schrank and Lomax, 2005). Traffic congestion causes travel delay and wastage of fuel thereby adding to the inconvenience and transportation expenses of the households owning vehicles. For instance, it has been found that traffic congestion caused 3.7 billion hours of travel delay and 2.3 billion gallons of wasted fuel for a total cost of more than $63 billion in the year 2003, which is an increase of 79 million hours and 69 million gallons respectively from year 2002 (Schrank and Lomax, 2005).

(2) Environmental Impacts

Automobile dependency has direct and indirect impacts on the environment. The direct impacts are caused by the vehicles primarily through vehicle travel, vehicle maintenance, vehicle manufacture and disposal of used vehicle and its parts. The indirect impacts of automobile dependency primarily include global warming.

Air pollution is one of the most significant environmental impacts directly caused by the vehicles. Specifically, vehicle travel produces harmful tailpipe and evaporative emissions such as carbon monoxide, nitrogen oxides, volatile organic compounds, sulfur oxides, particulates, carbon dioxide, methane, and toxic gases such as benzene (see EPA report, 1999). Other environmental impacts caused directly by the vehicles include negative effects of the releases during vehicle cleaning, maintenance, repair and refueling; land-filling of scrapped vehicles, pollution due to motor oil or lead-acid batteries disposal into the municipal waste stream, and emissions of toxic gases during the manufacture of vehicle and vehicle parts (see EPA report, 1999).

The primary environmental impact caused indirectly by vehicles includes global warming. Automobiles are major sources of greenhouse gases produced by burning of gasoline or diesel fuels that contributes to global warming (Harrington and McConnell, 2003; Small, 1997). Global warming can lead to significant changes in the regional climate.

(3) Health Impacts

The environmental impacts of automobile dependency have potentially serious implications on public health. The harmful mobile source emissions from the tail-pipe of vehicles can have significant impacts on public health, causing chronic respiratory illness, asthma attacks, respiratory restricted activity days, headaches and even premature deaths due to particulate emission from vehicles (Segal, 1999; EPA, 2006). Besides direct health-related impacts, automobile dependency also causes accidents and injuries from crashes. In the year 2002, around 40,000 people died in transportation crashes, while 3 million people were seriously injured, with 95% of these crashes occurring on the national highway (TR News, 2001).

(4) Impacts on the Economic Development

The automobile industry has been one of the most volatile sectors of the U.S. economy over the years. Specifically, the increasing dependence on automobiles has made the automobile industry very vulnerable to economic forces. This is because a large fraction of gasoline and a vast majority of vehicles used in the U.S are imported (Litman and Laube, 2002). Thus, an increase in gasoline price or vehicle price can significantly impact the U.S. economy by causing a decrease in the automobile sales and an increase in the transportation expenditures.

Additionally, the U.S. automobile industry faces fierce global competition, as indicated by the increasing demand for foreign cars over domestic cars. It has been found that increasing demand for foreign cars has lead to a decline in the employment opportunities in the U.S. automobile industry (Kubarych, 2004).

(5) Impacts on the Infrastructure

Automobile dependency has a direct impact on the existing infrastructure. Specifically, the increasing vehicular traffic spurred by automobile dependency is usually accommodated by increasing the road-space, increasing highway capacity, using an efficient traffic-monitoring system, and improving the maintenance of the infrastructure. However, due to financial and spatial constraints in the construction of new highways, often the transportation supply is not able to meet the transportation demand, leading to increasing traffic congestion problems and faster deterioration of the existing infrastructure. For instance, as the annual vehicle kilometers per capita increased from

8000 to 12000 kms, the annual per capita road expenditures in the U.S. increased only from $290 to $400 (Jeff *et al.,* 1997).

(6) Land Use Impacts

Land-use patterns are significantly affected by increasing dependence on automobiles (Litman, 1995) in at least two ways. First, a consequence of increasing vehicular traffic is the allocation of significant stretches of land to roads, highways and parking lots. Second, the willingness of the people owning vehicles to commute longer distances to meet their activity needs leads to suburbanization of residential developments (urban sprawl). These residential developments tend to be low-density automobile-oriented neighborhoods where accessibility via other modes of transportation, such as transit, is close to being non-existent.

(7) Impact on Energy Consumption

Automobiles depend heavily on fossil fuels as the source of energy. The increasing ownership of vehicles caused by automobile dependency has increased the demand for fuel. The Energy Information Administration (EIA) reported that the use of fuel by the transportation sector, which is primarily petroleum, has more than tripled from 1949 to 2001 (Schipper, 2004). In year 2002, EIA reported that the motorized vehicles consumed 13.1 million barrels per day, which accounts for two-third of the total petroleum consumption that year. The amount of consumption of energy has important fuel economy implications, primarily, protection of the environment from greenhouse effect, oil spills and pollution; conservation of the resources, reduction of oil imports and decrease in the fuel-related expenditures.

1.2 Vehicle Holdings and Usage – A Measure of Automobile Dependency

The wide-ranging impacts of automobile dependency at multiple societal levels (as discussed in the previous section) have serious policy implications. Hence, it is important to measure the degree of automobile dependency. Several indicators have been identified in the literature to assess the impacts of automobile dependency.[1] One of the most widely used indicators of household automobile dependency is the extent of household vehicle holdings and use. The vehicle holdings and/or usage of the household has also been considered one of most efficient and reliable measures of automobile dependency and used extensively to assess the various impacts of automobile dependency.

1.2.1 Importance of Vehicle Holdings and Usage

The subject of vehicle holdings and usage has been the focus of extensive research in the fields of economics, marketing and transportation. The multi-disciplinary nature of the research undertaken on vehicle holdings and usage indicates the diversity of its potential applications. This section addresses the importance of examining vehicle holdings and usage from different standpoints.

[1] They include vehicle ownership, vehicle usage, vehicle trips, competitiveness of alternate modes adjudged by the quality of their services, relative mobility of non-drivers compared to drivers, and market distortions favoring automobile use (VTPI, 2004).

(1) From a Travel Demand Modeling Perspective

Vehicle holdings and use have an important influence on almost all aspects of the activity and travel behavior of individuals and households. The statistics from NHTS data show an increasing dependence on personal-use motorized vehicles in the United States, with 92% of the American households owning at least one motor vehicle in 2001 (compared to about 80% in the early 1970s; see Pucher and Renee, 2003), and 59% of the households owning two or more vehicles. Further, the NHTS data shows that 87% of the daily trips in the United States are made by personal-use motorized vehicles, of which almost half are contributed by single-occupant vehicles (see Pucher and Renne, 2003). Household vehicle miles of travel have also increased 300% between 1977 and 2001 (relative to a population increase of 30% during the same period; see Polzin and Chu, 2004). In addition to the increase in the ownership and usage of vehicles, there is an increasing diversity in the body type of vehicles held by households. The NHTS data shows that about 57% of the personal-use vehicles are cars or station wagons, while 21% are vans or Sports Utility Vehicles (SUV) and 19% are pickup trucks. The increasing holdings and usage of motorized personal vehicles, combined with significantly low vehicle occupancy rates and the shift from small passenger cars to large non-passenger cars, has serious policy implications for traffic congestion, pollution, health, infrastructure, and energy consumption. The various policy implications of increasing vehicle ownership and usage, and its correlation with demographic characteristics of the household, vehicle attributes, fuel costs, travel costs, and the physical environment characteristics (land-use and urban form attributes) of the residential neighborhood, make it all the more challenging for travel demand modelers and economists to understand travel behavior and demand.

(2) From a Travel Demand Forecasting Perspective

Vehicle holdings and usage play a significant role in the conventional four step travel demand forecasting process used by most Metropolitan Planning Organizations (MPO). Specifically, the number of vehicles owned by the household influences three of the four steps, primarily trip generation, trip distribution and mode choice (CS, 1997) as discussed below:

- Trip Generation – It is reasonable to assume that the households that own many vehicles are more likely to make more number of trips. This might be because the availability of vehicles for more trip making purposes along with the convenience and time saved by using vehicles spurs more trips. The trip generation models that do not consider these factors underestimate the total number of trips generated (CS, 1997).
- Trip Distribution – Households that own vehicles are more likely to use their personal vehicles than transit in order to reach destinations not easily reached by transit. Hence, the number of vehicles owned by the household indirectly affects the choice of the destination of trips.
- Mode choice – It is natural to assume that households which own one or more vehicles are less likely to use transit as opposed to households with no vehicles.

Hence, the mode choice made by the households depends on the availability of vehicles by the household.

(3) From a Household Location Choice Modeling Perspective

The vehicle holdings of a household have an indirect effect on the household location choice. Specifically, the household's choice of residential location is influenced by accessibility of the workplace, shopping and schools, and availability of public transportation services (Kain, 1962; McFadden, 1977; Pagliara and Preston, 2003). Thus, households with more number of vehicles are able to live reasonably far away from work and reach their workplace in a reasonable amount of time. Also, households have a higher propensity to own more number of vehicles if the household members have long commute times from home to work (Bhat and Guo, 2005).

(4) From a Marketing Perspective

Vehicle type holdings and usage play a significant role in determining the consumer demand for different types of vehicles. This has important implications for car manufacturers. An understanding of the behavior of the automobile market helps car manufacturers make their vehicle supply decisions, including the production levels of different types of current vehicles and the attributes of the vehicles to be designed in the future. For instance, manufacturers are increasingly interested in promoting alternative-fuel vehicles. Hence, understanding the nature of the automobile market will enable the car manufacturers to predict the demand for these vehicles. Thus, from the perspective of car manufacturers, the preferences for different vehicle types in the overall population, and in demographic subgroups of the population, provide information to design future vehicles, to set production levels of different currently existing vehicle types, and to market vehicles by adopting appropriate positioning and targeting strategies.

(5) <u>From an Economic Development Perspective</u>

The automobile industry has been one of the most volatile sectors of the U.S. economy over the years. Specifically, the impact of changes in fuel price and vehicle price on the consumer demand for vehicles has made the automobile industry very vulnerable to economic forces (Litman and Laube, 2002). Thus, an understanding of vehicle holdings and usage which influence the consumer demand for vehicles will enable the economists to predict the impact of such variations on the U.S. economy.

(6) <u>From a Policy-Making Perspective</u>

The policy-makers are interested in understanding the implications of various policies aimed at decreasing the negative impacts of automobile dependency such as traffic congestion, fuel consumption and air pollution (see, for example, Small, 1997; Lave and Train, 1979; Feng *et al.,* 2004). Hence, accurate predictions of the sensitivity of vehicle holdings and usage of households to various possible policies would enable the policy-makers to make informed decisions. For instance, a 10% increase in the gasoline price might result in people choosing smaller vehicles over large vehicles (Lave and Train, 1979). This has important policy implications as it can be instrumental in reducing the total energy consumed by the vehicles (Lave and Train, 1979). Further, a higher price of gasoline can shift households out of choosing a combination of cars and SUVs into vehicle bundles that include only cars (Feng *et al.,* 2004). This shift in preference can help reduce mobile source emissions as cars (which have stricter emission standards than SUVs) produce lesser amount of pollutants than SUVs (Feng *et al.,* 2004).

Clearly, it is important to accurately predict the vehicle holdings of households as well as the vehicle miles of travel by vehicle type. The extent of accuracy of such predictions depends upon the number and type of dimensions used to characterize household vehicle holdings and use.

1.2.2 Dimensions Used to Characterize Vehicle Holdings and Usage

Several dimensions can be used to characterize household vehicle holdings and usage, including the number of vehicles owned by the household, type of each vehicle owned, number of miles traveled using each vehicle, age of each vehicle, fuel type of each vehicle and make/model of each vehicle. The most commonly used dimensions of analysis in the existing literature include (1) The number of vehicles owned by the household with or without vehicle use decisions (see Burns *et al.,*1976, Lerman and Ben-Akiva, 1976, Golob and Burns, 1978, Train, 1980, Kain and Fauth, 1977, Bhat and Pulugurta, 1998, Dargay and Vythoulkas, 1999, and Hanly and Dargay, 2000) and, (2) The type of the vehicle most recently purchased or most driven by the household. The dimension 'vehicle type' encompasses several aspects of the vehicle and varies depending upon its definition. The vehicle type may be characterized by body type (such as sedan, coupe, pick up truck, sports utility vehicle, van, etc; see Train, 1979, Kitamura *et al.,* 2000, and Choo and Mokhtarian, 2004), make/model (Mannering and Mahmassani, 1985), fuel type (Brownstone and Train, 1999; Brownstone *et al.*, 2000; Hensher and Greene, 2001), body type and vintage (Mohammadian and Miller, 2003b); and, make/model and vehicle acquisition type (Mannering *et al.,* 2002). Some studies have extended the analysis from choice of the most recently purchased vehicle to choice of all the vehicles owned by the household, and/or the usage of these vehicles. These studies include the joint choice of vehicle ownership level and vehicle body type (Hensher and Plastrier, 1985), vehicle body type and vintage (Berkovec and Rust, 1985), vehicle fuel type choice (Brownstone *et al.,* 1996), vehicle body type, vintage and vehicle ownership level (Berkovec, 1985), joint choice of vehicle body type and usage (Golob *et al.*, 1997; Feng *et al.,* 2004), vehicle make/model and vintage (Manski and Sherman, 1980; Mannering and Winston, 1985), vehicle ownership level, vehicle body type and usage (Train and Lohrer, 1982; Train, 1986), number of vehicles owned and usage (Golob and Wissen, 1989; Jong, 1990; Jong *et.al.*, 2004), and vehicle body type and usage (Bhat and Sen, 2006). A few other studies have examined the vehicle holdings of the household in terms of their vehicle transaction process based on vehicle transaction type, primarily, addition, replacement or disposal of the vehicle (Mohammadian and Miller, 2003a) or duration of vehicle ownership by vehicle type between two successive transactions (see, for example Jong, 1996; Gilbert, 1992; Bunch *et al.*, 1996).

The discussion above indicates that, while there have been several studies focusing on different dimensions of vehicle holdings and use, each individual study has either confined its alternatives to a single vehicle in a household or examined household vehicle holdings along a relatively narrow set of dimensions. This can be attributed to the computational difficulties in model estimation associated with focusing on the entire fleet of vehicles and/or using several dimensions to characterize vehicle type.

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1.3 Summary

The dependence of U.S. households on the automobile to pursue daily activity-travel patterns has been a subject of increasing research study in recent years because of the far-reaching impacts of this dependence at multiple societal levels (section 1.1.1). At the household level, automobile dependency satisfies the mobility and accessibility needs of the household members, but significantly impacts the transportation expenses of the household; at a community level, automobile dependency potentially encourages social stratification and inequity between different segments of the population; at a regional level, automobile dependency has significant impacts on traffic congestion, environment, health, economic development, infrastructure, land-use and energy consumption.

One of the most widely used indicators of household automobile dependency is the extent of household vehicle holdings and use. Vehicle holdings and usage plays a significant role in assessing the negative impacts of automobile dependency. In addition, it plays a vital role in travel demand modeling, travel demand forecasting, household location choice modeling, marketing, economic development and transportation policy analysis. The multi-disciplinary nature of the diverse applications of vehicle holdings and usage (section 1.2.1) along with its multiple dimensions that can be used to characterize it (section 1.2.2) make it a very challenging subject for research.

1.4 Research Objectives

The goal of this research is to contribute to the area of automobile demand modeling by developing a comprehensive econometric model to examine several dimensions of household vehicle holdings and usage decisions. In particular, we model number of vehicles owned as well as the following attributes for each of the vehicles owned: (1) vehicle body type, (2) vehicle age (i.e., vintage), (3) vehicle make and model, and (4) vehicle usage. The objectives of this study are as follows:

1. Develop a comprehensive conceptual framework of vehicle type/vintage and make/model choice and usage decision-making that incorporates all the observed and unobserved factors that potentially influence the decision of the household, while also considering (a) the processes that motivate the household to own and use multiple vehicle types, (b) the dynamics of vehicle ownership duration, (c) the influence of past vehicle ownership decisions, and (d) heterogeneity in the preferences of households.
2. Develop an econometric model to analyze the many dimensions of vehicle holdings and use. Specifically, the proposed econometric structure examines the simultaneous choice of multiple vehicle types/vintages and usage decisions by the household as well as the choice of a single make and model within each vehicle type/vintage chosen.

3. Estimate models using data from the Bay-Area Travel Survey, 2000 (BATS 2000) and examine the impact of factors such as household demographics, household head characteristics, household location characteristics, built environment characteristics of the residential neighborhood, vehicle attributes and fuel cost on the vehicle holdings and usage decisions.
4. Demonstrate the application of the model for evaluation of transportation policies. Specifically, the intent of this research is to highlight the impact of changes in built environment characteristics of the residential neighborhood and fuel cost on vehicle holdings and use of households.

1.5 Structure of the Dissertation

The rest of this dissertation is organized as follows: Chapter 2 presents a review on the state-of-the-art in automobile demand modeling, classified based on (1) the modeling methodology, (2) the application area and (3) the data used. Chapter 3 develops a comprehensive conceptual framework of vehicle holdings and usage decisions through the identification of the various modeling issues and factors that influences the decision-making. Chapter 4 presents the detailed mathematical structure formulated to analyze the many dimensions of vehicle holdings and use. Chapter 5 identifies the sources of data used in this analysis, describes the sample formation procedure and presents several descriptive statistics on the sample. Chapter 6 presents the empirical model estimation results and an application of the model using several policy simulations. Chapter 7 summarizes the important contributions of this research and identifies areas of further research.

Chapter 2. Literature Review

The field of automobile demand modeling has been of substantial interest to researchers in a wide variety of fields in the past several decades. The studies in this area span a wide range of modeling methodologies, a variety of application areas, and several types of data. In order to assimilate the contributions of this diverse body of research, the literature is classified into manageable categories for the purpose of this review. Specifically, the extensive body of literature is broadly classified based on (1) Modeling Methodology (2) Application area, and (3) Data type.

This chapter reviews the literature along each of these three dimensions of classification, and addresses the advantages and limitations of existing automobile demand models. The chapter ends by providing a summary of the extensive literature and positioning the current research within this broad context.

2.1 Classification Based on Modeling Methodology

Two different levels may be used to model the choice behavior of decision-makers. The first level is the aggregate level in which the choices of decision-makers are aggregated in some fashion and analyzed as a function of the characteristics of the alternative and socio-demographic characteristics of decision makers at the aggregated level. The most commonly used aggregate modeling approaches in vehicle choice modeling include aggregate time series, cohort models and aggregate car market models (see Jong *et al.,* 2004 for a detailed review of these approaches[2]). The second level to model choice behavior is the disaggregate level, in which the choice behavior is analyzed at the level of the decision-maker, as a function of characteristics of the alternatives and socio-demographic characteristics of each decision-maker.

The aggregate modeling approach has several disadvantages over the disaggregate modeling approach (Koppelman *et al.*, 2003). Specifically, the aggregate models that predict the choice behavior of the decision-maker at an aggregate level are unable to capture the factors influencing the choice behavior at the level of the decision-maker. The level of aggregation leads to considerable loss in variability, thus limiting the accuracy, versatility and policy sensitivity of aggregate modeling approaches (Kitamura and Bunch, 1992). Hence, the scope of the literature review in this dissertation is confined to disaggregate modeling approaches. The following sections discuss the disaggregate models used in the context of vehicle choice modeling, classified based upon the discrete and/or continuous nature of the choice alternatives, into (1) Discrete Choice models, and (2) Discrete-Continuous Choice models.

2.1.1 Discrete Choice Models

Discrete choice models are used to analyze and predict decision-maker's choice of one alternative (say, number of cars to own) from a finite set of mutually exclusive and collectively exhaustive alternatives (such as no cars, one car, two or more cars). The most commonly used discrete choice models in vehicle choice modeling are consistent with

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[2] Some of the recent applications of the aggregate modeling approach include Ingram and Liu (1997), Whelan *et al.* (2000), Whelan (2001), Dargay and Gately (1999), Berry *et al.* (1995) and Kveiborg (1999).

random utility maximization (RUM) theory. According to this theory, an individual will choose the alternative that maximizes his/her utility from among the set of available alternatives. Some of the widely used models are discussed below.

2.1.1.1 Multinomial Logit Model (MNL)

The MNL model, proposed by McFadden (1973), is the most commonly used model in vehicle type choice modeling (see Lave and Train, 1979; Mannering and Mahmassani, 1985; McCarthy, 1996; Manski and Sherman, 1980; Kitamura *et al.,* 2000; Choo and Mokhtatian, 2004; Brownstone *et al.,* 1996). The MNL assumes extreme-value distributed, and identically and independently distributed, error terms across alternatives and individuals. These assumptions lead to the simple and closed form mathematical structure for the choice probabilities in the MNL. The probability expression for choosing an alternative '*i*' from a set of J alternatives is:

$$P(i) = \frac{\exp(V_i)}{\sum_{j=1}^{J} \exp(V_j)}$$

Where $P(i)$ is the probability of the decision-maker choosing alternative i

and V_j is the systemic component of the utility of alternative j.

Though the closed form and ease of estimation of the logit model makes it a very desirable model, the Independence from Irrelevant Alternatives (IIA) property exhibited by the MNL restricts its application in the context of vehicle purchase/type choice models (Lave and Train, 1979; Bunch, 2000). The IIA property states that, for any decision-maker, the ratio of the probabilities of choosing two alternatives is independent of any other alternative. This property limits the applicability of the MNL model if the alternatives are correlated. For instance, in vehicle type choice modeling, some vehicle type alternatives such as hatchbacks and station wagons may be closer substitutes for each other than others such as pickup trucks and Sports Utility Vehicles (SUV).

2.1.1.2 Nested Logit Model

The Nested Logit (NL) Model, proposed by Ben-Akiva (1974), relaxes the rigidity of MNL models by allowing for covariance in random components among subsets (or nests) of alternatives. The nested structure is useful when the choice set is multi-dimensional (for instance, vehicle type and vintage choice). Additionally, the nested logit models have the advantage of retaining a closed form probability expression, which makes it a very desirable model structure for application in vehicle type choice modeling (McCarthy and Tay, 1998; Bunch *et al.,* 1993; Hensher and Plastrier, 1985; Mohammadian and Miller, 2003b; Hocherman *et al.*, 1983; Berkovec and Rust, 1985; Berkovec, 1985; Mannering *et al.,* 2002).

Notwithstanding the advantages of nested logit model, there are a few econometric limitations of this model form, including the following (1) These models cannot capture differential sensitivity across decision-makers (*i.e.* unobserved heterogeneity) to such vehicle characteristics as price, luggage capacity etc. (2) These models require the selection of a preferred nesting structure from a large number of plausible nesting structures based on the analyst's judgment. For instance, a choice set consisting of 5 alternatives can have as many as 50 possible 2-level nesting structures, 130 possible 3-level nesting structures and so on.

2.1.1.3 Ordered Response Logit/Probit Model

In contrast to the MNL and Nested Logit models, which are based on the random utility maximization theory, the ordered response choice models are based on the hypothesis that a uni-dimensional continuous latent variable represents the propensity of the decision-maker to make a choice (Bhat and Pulugurtha, 1998). For instance, let Y_i represent the number of vehicles owned by the household and Y_i^* represent the propensity of the household to own cars. Then $Y_i = k$ if and only if $\psi_{k-1} < Y_i^* \leq \psi_k \ \forall \ k = 0,1,.....,K \ (\psi_{-1} = -\infty, \psi_k = +\infty)$, where the ψ_k terms represent the threshold values of the latent propensity which demarcate the discrete outcomes. The latent propensity index Y_i^* is defined as the sum of a deterministic component and a random component. Several studies have used an ordered-response probit model for modeling the number of cars in the household (Kitamura and Bunch, 1992; Bhat and Pulugurtha, 1998; Hanly and Dargay, 2000). Some of these studies have included lagged variables to account for state dependence (*i.e.* dependence of current choices on past choices) and individual-specific error components to account for unobserved heterogeneity (*i.e.* unobserved variation in tastes across decision-makers) across households.

Though ordered response models have a simple model structure, Bhat and Pulugurtha (1998) consider them to be an over simplification and potentially inappropriate for vehicle ownership modeling. This is because of the relatively restrictive effects of exogenous variables imposed in the models. For instance, the Ordered Response Logit model can capture the monotonic increase of vehicle ownership with increase in the household income but it cannot capture the saturation effect in vehicle ownership when the household income is very high such that an increase in household income causes no change in the vehicle ownership level. Bhat and Pulugurtha's analysis indicated that unordered response models (such as the MNL) are superior to ordered response models.

2.1.1.4 The Mixed Logit Model

Mixed Logit models overcome the IIA restriction imposed by the standard logit model by allowing for random taste variation, non-proportional substitution patterns between alternatives, and correlation of the error components over time (Bhat, 1998; Bhat, 2003a; McFadden and Train, 2000). The first applications of mixed logit was apparently in the context of automobile demand models by Boyd and Mellman (1980) and Cardell and Dunbar (1980).

Mixed logit can be specified in two ways (or a combination of these): (1) Random-coefficient specification in which utility is specified as $U_{nj} = \beta_n x_{nj} + \in_{nj}$ with random β_n that varies over decision-makers, x_{nj} representing the observed variables that relate to the alternative and decision-maker and $\in_{nj}$ representing a random term that is iid extreme value, or an (2) Error-component specification in which utility is $U_{nj} = \alpha x_{nj} + \mu_n z_{nj} + \in_{nj}$, where α is a vector of fixed coefficients, and $\mu_n z_{nj} + \in_{nj}$ represents the unobserved portion of the utility which can be correlated over alternatives depending on the specification of observed variables, z_{nj}. Both these specifications are equivalent, but differ in interpretation (Bhat, 1998; Bhat 2003).

The advantages of the mixed logit model have been identified by several studies, some of which compared the estimation results of mixed logit models with standard discrete choice models (Brownstone and Train, 1999; Bhat, 1998; Bhat 2003; Brownstone *et al.*, 2000; Hensher and Greene, 2001; Train and Winston, 2004; Mohammadian and Miller, 2003a).

Brownstone *et al.* (2000) compared MNL and Mixed Logit models while modeling the choice of alternative fuel vehicles, and found the latter to provide better fits compared to the MNL. In addition, the mixed logit model indicated the presence of substantial heterogeneity in the respondent's preferences for alternative fuel vehicles. The non-IIA effects captured by the mixed logit model indicated that the market share for electric fuel vehicles comes disproportionately from other mini and subcompact vehicles, as expected.

Hensher and Greene (2001) compared nested logit and mixed logit models to analyze the choice of vehicles of different fuel types and found that nested logit models had a tendency to overestimate the number of households choosing alternative-fuels.

2.1.2 Discrete-Continuous Choice models

The discrete-continuous choice models are used to analyze and predict the simultaneous choice of the decision-makers of discrete-continuous alternatives where the discrete alternative is chosen from a finite set of mutually exclusive and collectively exhaustive alternatives. These models are important for accurate automobile demand modeling because households are likely to simultaneously make the discrete choice of the vehicles to own and a continuous choice of annual usage to jointly maximize utility. For instance, a household chooses to own a SUV as it is more likely to have a high usage of the vehicle. The modeling efforts in the context of vehicle type and usage decisions are discussed below.

2.1.2.1 Regression

Regression models have been widely applied in automobile demand literature to predict the vehicle miles traveled (VMT) by the household. Though regression models essentially estimate the continuous choice of vehicle usage, it can be integrated with discrete choice models to jointly analyze the choice of vehicle type and usage. For instance, Jong (1996) used regression equations for estimating vehicle usage and fuel efficiency and integrated these models with vehicle holding duration and vehicle type choice models.

Regression estimation aims at understanding the relationship between a dependent variable, Y (VMT in this case) and a set of independent variables, X . These equations are specified as the following:

$Y = \beta X + \in$, where $\in$ denotes a random term.

Several studies have used parametric regression to predict VMT (Hansen and Huang, 1997; Kockelman, 1997, Pickrell *et al.* 1998; Kitamura *et al.,* 2000). The studies by Chow (1957) and Wharton (1977) are among the first aggregate studies that used regression models for studying the automobile market.

Some other studies have used nonparametric regression to analyze VMT as they perform better than ordinary-least squares (OLS) by allowing for full distributional flexibility of error terms and enhancing the goodness of model prediction (Kweon *et al.*, 2004).

2.1.2.2 MNL/NMNL with Conditional Utility Function

Standard discrete choice models derived from conditional utility function have a modeling structure that can jointly accommodate the discrete choice among vehicle bundles and a continuous choice of miles. This modeling structure is essentially the first step towards dynamic discrete-continuous models (Dubin and McFadden, 1984). For ease of understanding the modeling framework, the model structure used in Train and Lohrer (1982) is discussed below.

Train and Lohrer (1982) formulated a dynamic discrete-continuous model based on the assumption that a household will choose the number of vehicles to own, the class/vintage of each vehicle, and the make/model of each vehicle such that its conditional utility is maximized. They proposed that given a household owns n vehicles of class/vintage c and make/model m, the conditional indirect utility function of the household can be expressed as a function of its income, *Y*, price of travel, *P* and other explanatory variables, *x*, as shown below.

$$V_{n,c,m} = f(Y, P_{n,c,m}, x_{n,c,m})$$

The number of miles traveled by the household using its *i*th vehicle was then derived using Roy's identity, from microeconomic demand theory (the negative of the derivative of the conditional indirect utility function with respect to the price per mile of traveling by the vehicles, divided by the derivative with respect to income) as shown below:

$$VMT^{i}_{n.c.m} = -\frac{\partial V_{n.c.m} / \partial P^{i}_{n,c,m}}{\partial V_{n,c,m} / \partial Y} = g(Y, P_{n,c,m}, x_{n,c,m})$$

where i = 1, 2,…,n

The choice models were then derived from these equations by maximizing the conditional utility function. A generalized extreme value structure for the error component condenses the choice models to a logit form.

Some of the studies that used a similar modeling structure in automobile demand modeling include Goldberg (1998), West (2004), Train (1986), Hensher *et al.* (1992), Feng *et al.* (2004), Jong (1990) and Mannering and Winston (1985). All these studies except for Feng *et al.* (2004) use a sequential estimation procedure, which can lead to inconsistent standard error estimates and therefore, incorrect inferences regarding the significance of variables.

2.1.2.3 Duration Models

Hazard based duration models are used to analyze the time duration between two vehicle transactions. The duration models are based on a hazard function *h(t)*, which gives the probability of exit from the state immediately after time *t*, given that the state is occupied in state *t* (see Hensher and Mannering, 1994 and Bhat, 2000a for duration model reviews in Transportation). The hazard function can be written as a function of the distribution function *F(t)* and the probability density function *f(t)* of the variable *T* given as:

$$h(t) = f(t)/\{1 - F(t)\}$$

The $h(t)$ function takes different functional forms such as exponential, weibull, log-normal etc. Jong (1996) used several functional forms for the hazard function and found the weibull model (with time-varying covariates such as fuel price index and without heterogeneity) to be the most effective model. Similar studies that have used hazard models to explain vehicle ownership duration include Gilbert (1992), Bunch *et al.* (1996), Yamamoto *et al.* (1999) and Yamamoto and Kitamura (2000).

Composite models of duration and discrete choice models have not yet been explored in automobile demand modeling literature. However, studies undertaken in other fields have developed joint models of duration and discrete choice (Bhat, 2000a; Chintagunta and Prasad, 1998; Kuo and Chen, 2004). These composite models can represent choice situations defined by choice of a single alternative from a finite set of alternatives. However, modeling of choice situations where multiple alternatives are simultaneously chosen from a set of alternatives, as is typical of the vehicle holdings and usage decision-making process of household, becomes very cumbersome with these models.

2.1.2.4 Other Models

A number of other discrete-continuous models have been used in the vehicle ownership literature. Several studies have used structural equation models to study household vehicle usage behavior (Golob, *et al.*, 1996; Golob, 1990; Golob, 2003), joint choice of vehicle ownership and usage (Golob and Wissen, 1989) and joint choice of vehicle type and usage (Golob *et al.*, 1997). Some others used simultaneous equation systems to study vehicle usage (Mannering, 1983; Mannering, 1986; Hensher, 1985).

2.1.2.5 Multiple Discrete-Continuous Models

The aforementioned conventional discrete-continuous models analyze situations in which the decision-maker can choose only one alternative from a set of mutually exclusive alternatives. These models are based on the assumption that the choices are perfect substitutes of each other. This is not representative of the choice situation of multiple-vehicle households, where households own and use multiple types of vehicles simultaneously to satisfy various functional needs of the household. The analysis of such choice situations require models that recognize the multiple discreteness in the mix of vehicles owned by the household.

Models which recognize multiple-discreteness have been developed recently in the field of marketing science. Hendel (1999) and Dube (2004) considered the purchase of multiple varieties within a particular product category as the result of a stream of expected (but unobserved to the analyst) future consumption decisions between successive shopping occasions (see also Walsh, 1995). Due to varying tastes across individual consumption occasions between the current shopping purchase and the next, consumers are observed to purchase a variety of goods at the current shopping occasion. The above studies use a linear utility function at each individual consumption occasion, with the utility parameters varying across consumption occasions. A Poisson distribution is assumed for the number of consumption occasions and a normal distribution is assumed regarding varying tastes to complete the model specification. Such a "vertical" variety-seeking model may be appropriate for frequently consumed grocery items such as carbonated soft drinks, cereals, and cookies. However, in many other choice occasions, such as usage of different types of vehicles owned by the household, the true decision process may be better characterized as "horizontal" variety-seeking, where the consumer selects an assortment of alternatives due to diminishing marginal returns *(i.e.*, satiation) for each alternative.

Kim *et al.* (2002) proposed a translated non-linear, but additive utility structure for such "horizontal" variety-seeking that accommodates multiple-discreteness as well as satiation behavior. Bhat (2005) used the same non-linear utility function form as in Kim *et al.* (2002), but formulated a simple and parsimonious closed form Multiple Discrete-Continuous Extreme Value (MDCEV) model which collapses to an MNL choice model in the case of single discreteness. Specifically, the MDCEV model incorporates a multiplicative log-extreme value error term in the utility function. The result of such a specification is a surprisingly simple closed form expression for the discrete-continuous probability of not consuming certain alternatives and consuming given levels of the remaining alternatives. Further, Bhat (2005) proposed a mixing distribution to accommodate heteroscedasticity and covariance in unobserved characteristics affecting the demand for different alternatives, leading to the Mixed MDCEV (or MMDCEV) model structure. Estimation of the MDCEV model was straightforward and easily achieved using a maximum likelihood inference procedure, while estimation of the MMDCEV model was accomplished using a simulated maximum likelihood procedure. Bhat (2005) applied this model in the context of individual time use allocation in different types of discretionary activity pursuits. The application of these multiple discrete-continuous models is yet to be explored in automobile demand modeling.

The MDCEV and other multiple discrete-continuous models do not, however, accommodate a choice situation characterized by the joint choice of (1) multiple alternatives from a set of mutually exclusive alternatives, and (2) a single alternative from a set of mutually exclusive alternatives. Such a choice situation better characterizes the decision-making process of a multiple vehicle household. For instance, a household might choose to own multiple vehicle types such as an SUV, a Sedan and a Coupe from a set of mutually exclusive vehicle types because they serve different functional needs of individuals of the household. But within each of the vehicle types, the household chooses a single make/model from a vast array of alternative makes/models.

2.2 Classification Based on Application Area

The vast application of vehicle choice modeling ranges from predicting how many/type/make and models/annual usage of vehicles are owned by the household to the change in the vehicle fleet mix of households over a period of time. Based upon the application area, the literature in vehicle choice modeling can be broadly classified in two categories: (1) Static Models (2) Dynamic Models.

2.2.1 Static Models

The static models predict the choice of vehicle number/type/make and model and/or usage. These models are considered static in nature because they are based on the assumption that for a given period of time the household compares all vehicles or combinations of vehicles (for households with multiple vehicle holdings) and chooses the alternative which maximizes the utility. Hence, the static equilibrium assumption restricts these models to predict the vehicle fleet of households for a given period of time only (Jong and Kitamura, 1992). The static models include vehicle ownership models, vehicle purchase models and vehicle holdings and/or usage models.

2.2.1.1 Vehicle Ownership Models

The vehicle ownership models predict the total number of vehicles owned by the household. The earliest studies in vehicle ownership include Burns *et al.* (1976), Lerman and Ben-Akiva (1976), Golob and Burns (1978), Train (1980) and Kain and Fauth (1977). The most commonly used modeling structures are MNL and ordered response models. Studies indicate that the MNL is more appropriate for modeling vehicle ownership (Bhat and Pulugurta, 1998).

Vehicle ownership models examine the number of vehicles owned by the household as a function of the household socio-demographic characteristics. Some studies have also incorporated the number of vehicles owned in the previous year as lagged endogenous variable to capture the persistence in vehicle ownership and found it to be extremely significant (Dargay and Vythoulkas, 1999; Hanly and Dargay, 2000). These models do not take into consideration the characteristics of the vehicles or other econometric issues relevant to appropriately capturing dynamic effects.

2.2.1.2 Vehicle Purchase Models

The vehicle purchase models usually predict the choice of the most recent vehicle (classified by body type, make/model or vintage, or vehicles classified by fuel type) purchased most recently by the household. The vehicle purchase models do not give attention to the number/type and usage of other vehicles owned by the household. The literature found on vehicle purchase models can be classified into:

- Vehicle type choice characterized by body type, make/model or vintage (Lave and Train, 1979; Kitamura *et al.,* 2000; Page *et al.,* 2000, Manski and Sherman, 1980, Mannering and Mahmassani, 1985, Mccarthy, 1996; McCarthy and Tay, 1998; Bunch *et al.,* 1993; Birkeland and Jørgensen, 2001; Mohammadian and Miller, 2003b; Train and Winston, 2004)

- Vehicle type choice characterized by fuel type (Brownstone and Train, 1999; Brownstone *et al.*, 2000, Hensher and Greene, 2001)
- Joint choice of vehicle make/model/vintage and vehicle acquisition type (Mannering *et al.,* 2002)
- Choice of vehicle type most driven (Choo and Mokhtarian, 2004)

The MNL is the most commonly used model for predicting vehicle purchase decision of households (Lave and Train, 1979, Mannering and Mahmassani, 1985, Mccarthy, 1996). Other vehicle purchase models include nested logit models (McCarthy and Tay, 1998; Bunch *et al.,* 1993) and mixed logit models (Train and Winston, 2004; Brownstone and Train, 1999; Brownstone *et al.*, 2000, Hensher and Greene, 2001). The variables used in these models include socio-demographic characteristics of the household, locations characteristics and vehicle attributes.

The definition of the choice set is the most important concern of vehicle purchase models. In order to reduce the complexities associated with large choice sets, several studies have clubbed the makes/models of vehicles into classes by calculating average vehicle characteristics for each class (Lave and Train, 1979), or using sampling procedure to randomly generate choice sets (Mannering and Mahmassani, 1985, McCarthy, 1996). The models estimated using these choice sets is consistent but not necessarily efficient (Bunch, 2000).

2.2.1.3 Vehicle Holdings and/or Usage Models

The vehicle holdings and/or usage models predict (1) the vehicle type (defined by body type, make/model, class and/or vintage) and/or (2) annual usage of all the vehicles owned by the household, based on the assumption that households re-decide these decisions for its entire fleet on an annual basis so as to maximize utility (Bunch, 2000). These models examine the effect of various vehicle attributes (such as purchase price, fuel cost, vehicle dimensions), household socio-demographic characteristics (such as income, household size) and household location characteristics on vehicle demand.

The extensive literature on vehicle holdings and/or usage models can be classified by their application area into the following:

(1) Vehicle holdings model:

- Choice of vehicle type conditional on number of vehicle owned by the household (Manski and Sherman, 1980; Hensher and Plastrier, 1985; Berkovec and Rust, 1985)
- Choice of vehicle fuel type conditional on number of vehicle owned by the household (Brownstone *et al.,* 1996)
- Joint choice of vehicle type and vehicle ownership level (Berkovec, 1985)

(2) Vehicle holdings and usage model:

- Joint choice of vehicle type and usage (Golob *et al.*, 1997; Mannering and Winston, 1985; Feng *et al.,* 2004)
- Joint choice of number of vehicles owned, vehicle type and usage (Train and Lohrer, 1982; Train, 1986)

- Joint choice of number of vehicles owned and usage (Golob and Wissen, 1989; Jong, 1990)

The <u>vehicle holdings</u> models have the following three limitations: First, practically all the studies examining vehicle holdings have neglected households owning more than two vehicles. This omission can lead to problems in cities like California where a significant number of households own three or more vehicles. Second, the alternatives considered in a vehicle holdings model may not be mutually exclusive. For instance, if a household owns an old coupe, a new coupe and a new SUV, ignoring the vintage of the vehicles in the choice set can lead to biased estimates. Hence, to avoid bias in the estimation results, these models require complex nesting of the alternatives that is not incorporated in the existing models. Third, these models ignore usage decisions of the household. Since these decisions are made simultaneously along with the vehicle purchase decisions, omitting the usage variable leads to inaccurate estimates.

The <u>vehicle holdings and usage</u> model literature has attempted to address the aforementioned concerns in two ways. First, the vehicle holdings and usage model takes into consideration the existing fleet owned by the households, characterized primarily by the body type, make/model and vintage. The detailed characterization ensures that the alternatives in the choice set are mutually exclusive. Since multiple vehicle households own a mix of different vehicle types, the choice set size becomes huge due to combinatorial effects, leading to complexity in the modeling framework. Second, discrete-continuous models are used for estimation purposes as these models predict the discrete choice of vehicle bundle and a continuous choice of vehicle usage. The continuous dimension of the econometric models makes the estimation process cumbersome.

2.2.2 Dynamic Models

The dynamic models, also known as vehicle transaction models, predict the change in the vehicle fleet mix between two given points in time. As opposed to static vehicle models, these models are more closely tied to the household decision-making process. The development of these models is based on the fact that the household vehicle fleet in not acquired instantaneously. Instead, the household vehicle fleet is the result of series of transaction decisions to acquire, replace, and dispose of household vehicles (Jong and Kitamura, 1992).

Vehicle transaction models can be broadly represented in two ways (1) frequency and types of transaction events per unit time interval (2) duration between two successive vehicle transactions types. Both of these specifications require detailed data on the vehicle transaction that is very difficult to obtain (since most available data are cross-sectional). Hence, relative to the vast number of studies undertaken in the context of static vehicle models, very few vehicle transaction modeling studies have been developed. The vehicle transaction modeling literature can be classified into the following:

(1) Vehicle transaction type choice (Mohammadian and Miller, 2003a)

(2) Vehicle transaction type (addition or replacement of vehicle) and vehicle type choice (Hocherman *et al.*, 1983)

(3) Vehicle scrappage models (Jong, *et al.*, 2001; Park, 1977; Hensher *et al.,* 1992)

(4) Duration of vehicle ownership (Jong, 1996; Gilbert, 1992; Bunch *et al.*, 1996; Yamamoto *et al.*, 1999; Yamamoto and Kitamura, 2000)

(5) Vehicle transaction type and duration (Jong and Kitamura, 1992)

The modeling structures used for estimation purposes for the first three types of dynamic models primarily include MNL (Jong, *et al.*, 2001), Nested Logit (Hocherman *et al.*, 1983) and Mixed Logit models (Mohammadian and Miller, 2003a); while the fourth type was estimated using a duration model. The modeling structure for the last type of dynamic models, proposed by Jong and Kitamura (1992), included a joint model with a non-IIA choice model (such as nested logit model) to analyze the vehicle transaction type choice and a discrete-time frequency model to analyze duration between two successive vehicle transaction types. Discrete-time frequency models are based on the assumption that the vehicle holdings are observed (by the analyst) at equi-spaced discrete time points (say, a year) and the transactions that took place between the time points identified (Jong and Kitamura, 1992). A discrete-time frequency model was chosen over duration model to analyze the duration of vehicle ownership because the duration models in its most typical form assume no change in exogenous variables between two transactions. For instance, if a duration model includes household income and fuel price as exogenous variables, then it assumes that there is no change in these variables during the entire duration that a vehicle is held. This clearly appears to be a restrictive assumption.

Further, formulation of a duration model that accounts for changes in the exogenous variables requires detailed data on the timings of the change which is practically impossible to obtain.

2.3 Classification Based on Data

Data plays a significant role in deciding the structure of the model and its application. For instance, some modeling structures such as duration models and application areas such as vehicle transaction models are data-intensive. Hence, availability of the appropriate data is extremely important. The studies can therefore be categorized depending upon their data needs by (1) survey type and (2) type of observations.

2.3.1 Data Defined by Survey Type

The data for vehicle ownership is usually collected using one of two types of surveys: (1) Stated preference (SP) surveys and (2) Revealed Preference (RP) surveys. In SP surveys, the respondents are asked to choose from hypothetical vehicle descriptions (Brownstone *et al.*, 1996; Jong *et al.,* 2001; Brownstone *et al.,* 2000; Louviere *et al.,* 2000), while in RP surveys they are asked to give information about their existing vehicle fleet. Depending on the data obtained from the surveys, the literature can be classified into studies which developed models based on (1) SP data (2) RP data (3) Joint SP and RP data.

SP data models are sensitive to the choices of the vehicles that are new in the market, for instance, alternative-fuel vehicles (Brownstone and Train, 1999; Hensher and Greene, 2001; Bunch *et al.*, 1993). However, SP data may not be appropriate for modeling purposes because of two reasons. First, the preference of the respondents will be dubious considering the fact that some of the attributes listed in the SP surveys are for the vehicles in the future market and hence not easily understood by the respondents. This can lead to uncertainty and bias in the model estimation. Second, the response of the respondents in the survey might not be same as what they do in real life. For example, respondents might opt for a vehicle which leads to zero pollution thinking of the general public good, but might not actually go for an electric vehicle (Brownstone *et al.,* 2000).

RP data models, as opposed to SP data, are critical to understand realistic vehicle-type choice of households. However, there are some limitations associated with RP data too. First, RP data is plagued by multicollinearity and has limited variation in the attributes (Brownstone *et al.*, 2000). Second, definition of choice sets in RP data models requires attention in order to obtain unbiased model estimation results. Specifically, choice sets are generated either by clubbing the alternatives into broader categories based upon similarities in their characteristics or by random sampling of alternatives because large choice sets can create computational difficulties for model estimation. Third, RP datasets necessitate linking physical attributes from external databases, which leads to an approximation of the choice situation faced by the decision makers. Notwithstanding the drawbacks associated with RP data models, the ease of availability and usefulness of the data makes it the basis of most of the studies in the automobile demand literature.

Though RP data models form the backbone of most of the studies, many recent studies are exploring the combination of SP and RP data. Studies show that such a dataset is best for forecasting purposes because RP data captures the real-world preferences of the households of vehicles and SP data captures the preference of the households for future vehicles (Brownstone *et al.*, 2000; Golob *et al.*, 1997). However, combining RP and SP data leads to some econometric issues and challenges. These include the issues of difference in scaling, correlation in unobserved attributes across repeated choices made by the decision makers and unobserved correlation between SP and RP choices (Bhat and Castelar, 2002; Brownstone *et al.,* 2000; Hensher and Greene, 2001).

2.3.2 Data Defined by Type of Observations

The vehicle ownership studies can be characterized by the type of observations recorded in the dataset into three categories: (1) Cross-sectional data (2) Panel data and (3) Pseudo Panel data. Cross-sectional data is based on the assumption that at a given point in time, a cross-section of the households is able to capture the various characteristics of the household. Hence, these datasets include information on the existing vehicle fleet mix, socio-demographic and location characteristics of the individual at a particular point in time. Though these datasets are easily available and usually detailed, models based on this data are not able to capture the long-run relationships since such relationships are not constant with time. As opposed to cross-sectional data, panel data and pseudo panel data are rarely available.

Panel datasets[3] comprise of repeated observations of same behavioral units over time, making it easier to understand the behavioral changes to ownership of cars over a period of time. It enables incorporation of inter-temporal dimensions present in car ownership choice such as resistance to changes in ownership levels such as search costs and intra-temporal dimensions such as acquired taste of lifestyle (Nobile *et al.,* 1996). These datasets can cause bias in the model estimates due to attrition since the size and representativeness of the sample declines with time. Panel data models are usually used to study the persistence of vehicle ownership over time (Bjorner and Petersen, 2004).

Pseudo panel datasets[4] or repeated cross-sectional data, is based on "grouping individuals or households into cohorts defined on the basis of common shared characteristics and treating the averages within these cohorts as observations in a panel" (Dargay and Vythoulkas, 1999). These cohorts are based on time-invariant characteristics of the household and are followed over time in cross-sectional datasets. However, creating cohorts leads to loss of information since it requires tradeoff between the size and number of cohorts.

The limited availability of panel and pseudo panel datasets make it less promising for modeling purposes. Hence, cross-sectional data forms the basis of most of the studies undertaken in the field of automobile demand modeling.

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[3] Some of the studies which used panel data include Kitamura and Bunch (1992), Meurs (1991), Meurs (1993), Golob (1990), Kitamura (1989) and Yamamoto and Kitamura (2000).

[4] Some of the studies which used pseudo-panel data include Gallez (1994), Madre (1990) and Jansson (1989).

2.4 Summary and Contributions of Current Research

The earlier studies discussed above have provided important insights into the field of automobile demand modeling along each of the three dimensions of modeling methodology, application area and data.

(1) Modeling Methodology

Standard discrete choice models (multinomial logit, nested logit or mixed logit) are the most commonly used automobile demand models. The literature on vehicle ownership, vehicle type choice and/or usage models indicate an extensive use of these models. Specifically, all of these studies used standard choice models for the vehicle type dimension and a continuous linear regression model for the vehicle use dimension (if this second dimension is included in the analysis). Some of the other studies also used standard discrete choice models to examine vehicle transaction type choice, while a few others used duration models to examine the vehicle transaction behavior.

The studies that have used standard choice models (where one and only one alternative out of several is selected) do not recognize intrinsic multiple discreteness in the mix of vehicle types held by households. That is, these studies do not consider that households own a mix of vehicle types to satisfy different functional or variety-seeking needs. Additionally, these studies do not recognize that there is diminishing marginal returns (*i.e.*, satiation) in using a single vehicle type, which may be the fundamental driving force for households holding multiple vehicle types. The standard discrete choice models are not equipped to handle multiple discreteness or satiation effects, which limits the application of these models.

(2) Application Area

The literature review shows that most of the studies have examined the vehicle ownership level of households or the type of the most recent vehicle purchased. Some other studies have considered the vehicle type holdings and/or usage of the all the vehicles owned by the household while few others have examined the vehicle transaction process of the households. Alternatively, most of the studies do not examine the dynamics of vehicle transaction behavior (*i.e.* are static in nature).

Additionally, the literature indicates that the vehicle type and usage models are the most comprehensive automobile demand models based upon the number of dimensions jointly examined by these models, including number, type (characterized by body style) and usage of the vehicles. These dimensions represent only a few of the several dimensions along which automobile demand can be examined such as vintage, make/model, trip purpose, fuel type, vehicle transaction type and duration of vehicle ownership. In other words, few dimensions have been used in the state-of-the-art vehicle type and usage models because of computational difficulties in model estimation associated with using several dimensions. This restricts the application area of automobile demand models.

(3) Data

Notwithstanding the drawbacks associated with RP data models, the ease of availability and usefulness of the data makes it the basis of most of the studies in the automobile demand literature. Some recent studies are exploring the combination of SP and RP data. Studies show that such a dataset is best for forecasting purposes because RP data captures the real-world preferences of the households of vehicles and SP data captures the preference of the households for future vehicles. However, combining RP and SP data leads to some econometric issues and challenges.

The insights from the earlier studies in automobile demand modeling summarized above gives us a good understanding of the advantages and limitations of existing automobile demand models. The intent of this research is to contribute to this growing area of research in the area of vehicle holdings and use in many ways. First, we use several dimensions to characterize vehicle holdings and use. In particular, we model number of vehicles owned as well as the vehicle body type, vehicle age (*i.e.* vintage), vehicle make and model, and vehicle usage, for each of the vehicles owned. Second, we develop a conceptual framework to examine vehicle holdings and use that incorporates a comprehensive set of determinants of vehicle holdings and usage decisions, including household demographics, individual characteristics, vehicle attributes, fuel cost, and built environment characteristics (see chapter 3). Third, we use an econometric formulation to analyze the many dimensions of vehicle holdings and use. Specifically, we formulate a flexible, multiple-discrete continuous econometric model that builds upon the state-of-the-art in choice modeling and explicitly addresses the issue of households potentially holding a mix of different vehicle types, vintages, makes and models, jointly with the annual miles of use of each vehicle type/vintage (see chapter 4).

Chapter 3. Conceptual Framework

The objective of this chapter of the dissertation is to develop a comprehensive conceptual framework for the choice of vehicle holdings and usage decisions. The review of the extensive literature on automobile demand modeling presented in the previous chapter contributes toward this objective by identifying the key issues related to an understanding of vehicle holdings/usage decisions. In this chapter, we present a clear picture of vehicle holdings and usage decisions and analyze the key issues (section 3.1), propose a comprehensive list of factors that influence the vehicle holdings and usage decisions (section 3.2), and develop a conceptual framework that is exhaustive and complete in its consideration of causal factors (section 3.3).

3.1 Understanding the Vehicle Holdings and Usage Decisions

In the process of developing a better understanding of vehicle holdings and usage decisions, we identified several key issues that need to be considered to generate a comprehensive conceptual framework for modeling the choice. We discuss these issues in the following sections.

3.1.1 Simultaneity in Decision-Making

The primary vehicle holdings and usage decisions made by the household include (1) the number of vehicles to own, (2) the type of vehicles to own, and (3) the rate of usage of each of the vehicles. These three decisions are very likely to be made simultaneously by the households. In order to understand this, let us consider the decision-making process of households for owning vehicles. The households decide to purchase single or multiple types of vehicles so that they can meet their mobility and functional needs. In order to satisfy these needs, the household uses each of its vehicle types. Specifically, the household tries to maximize its utility from owning different types of vehicles by using them to an optimum level. At the same time, the optimum usage of the vehicles by the household is influenced by the characteristics of the vehicle types purchased by the households. This clearly indicates that the vehicle type and vehicle usage decisions are dependent on each other. The dependency of these primary decisions have been recognized and addressed by several studies (Bunch, 2000; Golob *et al.*, 1997; Mannering and Winston, 1985; Feng *et al.,* 2004; Train and Lohrer, 1982; Train, 1986).

Besides the primary decisions, the households also make several other decisions such as choice of the make/model of the vehicle, duration of ownership of the vehicle, and transaction decisions *i.e.* to add/dispose/replace a vehicle in the vehicle fleet. The order in which these decisions are made is not clear and there has been no proof that any particular sequence of decisions is more likely than the other.

3.1.2 The Choice situation – Imperfect and Perfect Substitutes

An important issue in the analysis of choice behavior of any kind is the characterization of the choice situation. One of the several ways of defining the choice situation is by the concept of substitutability. The choice situation can be characterized by (1) choice of one alternative from a set of mutually exclusive alternatives *i.e.* assume that the alternatives are perfectly substitutable for each other, also called single discreetness (2) choice of multiple alternative from a set of mutually exclusive alternatives *i.e.* assume that the alternatives are imperfect substitutes for one another, also called multiple discreetness. Both these choice situations are applicable in the context of vehicle holdings and usage modeling. For instance, a household might choose to own multiple vehicle types such as SUV, Sedan and Coupe from a set of mutually exclusive vehicle types. The simultaneous demand for multiple vehicle types indicates that they are 'imperfect substitutes' of each other in that they serve different functional needs of individuals of the household. At the same time, the household also chooses the make/model for each of the vehicle types. The choice of only one make/model from a subset of alternatives indicates that the various make/models available to the household for a particular vehicle type are 'perfect substitutes' of each other. Hence, in the context of vehicle holdings and usage modeling, the choice situation can be characterized by joint choice of imperfectly and perfectly substitutable alternatives. Such choice situations cannot be handled by classical discrete and discrete-continuous models which assume that the alternatives are perfect substitutes of each other.

3.1.3 Satiation

As discussed in the previous section, the choice of different vehicle types by the household in order to meet different functional needs is characterized by the choice of multiple vehicle types simultaneously. The simultaneous demand for multiple vehicle types as opposed to a single vehicle type suggests that the marginal utility from using a single vehicle type decreases with the increasing usage of that vehicle type (*i.e.* satiation effects), driving the household to own multiple vehicle types.

Satiation effects can be broadly defined as the diminishing marginal returns from an alternative as the consumption of that alternative increases (Kim, 1992; Bhat, 2005). Satiation effects lead to the preference of a household to own one or more vehicle types. For instance, a household will use only one vehicle type for all its travel needs if the household is not satiated by the usage of that vehicle type and is willing to continue using it (*i.e.* a low rate of satiation). On the other hand, a household is more likely to use multiple vehicle types if the household is satiated with the increasing use of a single vehicle type because each vehicle type may be geared toward a particular functional need. For instance, a household owning a sedan, a minivan and a pickup truck may use the sedan for work-related and shopping trips, the minivan for recreational trips with the family, and the pickup truck for hauling heavy luggage.

The satiation effects can vary across households depending upon the socio-demographic characteristics of the household. The incorporation of these effects in vehicle type choice models requires a non-linear structure for the utility function. This is in contrast to standard vehicle type choice models that assume a linear utility structure (*i.e.* no satiation effects).

3.1.4 Duration Dynamics and State Dependence

The number of vehicles held by the households at any point in time is not acquired instantaneously by the household but is a result of series of transaction decisions which are conditioned on the current vehicle holdings (Jong and Kitamura, 1992). From this standpoint, household vehicle ownership is a dynamic behavioral process that evolves over time.

Most of the vehicle ownership models have focused on a single year as the time period for analysis of vehicle ownership behavior. Such single year analyses assume uniformity and/or behavioral independence in the vehicle ownership decisions from one year to the next (Bhat *et al.,* 2005b). Both these assumptions do not provide a realistic representation of the decision-making process of households. For instance, it is reasonable to expect year to year variation in the vehicle ownership of household (*i.e.* variation in the duration of ownership of different vehicles of the household) depending upon their functional and variety seeking needs, socio-demographic characteristics and the vehicle attributes (see for example Jong, 1996; Gilbert, 1992; Bunch *et al.*, 1996; Yamamoto *et al.*, 1999; Yamamoto and Kitamura, 2000). Also, it is logical to assume that existing vehicle ownership of the households is influenced by past vehicle ownership (this phenomenon is also referred to as state dependence). Several studies have clearly indicated the persistence of vehicle ownership of households across time (Dargay and Vythoulkas, 1999; Bjorner and Petersen, 2004).

Hence, it is important that vehicle ownership models explicitly accommodate (1) the duration dynamics which explains the year to year variation in vehicle ownership behavior and (2) the state dependence which explains the influence of past vehicle ownership decisions on the current vehicle ownership. This can lead to better and unbiased estimations of the effect of time on the changes in the vehicle ownership of households.

3.1.5 Observed and Unobserved Heterogeneity

Heterogeneity refers to observable (to an analyst) or unobservable (to an analyst) variations in tastes across households. There are two types of heterogeneity: observed heterogeneity and unobserved heterogeneity (see Bhat, 2000b; Leszczyc and Bass, 1998 to distinguish between observed and unobserved heterogeneity). Observed heterogeneity in vehicle type choice is caused by factors such as household socio-demographics (income, household size, ethnicity etc), residential location characteristics and vehicle attributes (purchase price, engine size, brand loyalty etc.). This heterogeneity may be incorporated in the vehicle type choice models by introducing observed household socio-demographic characteristics and residential location characteristics as alternative-specific variables and by interacting vehicle attributes with observed household/residential characteristics (Bhat, 2000b). Unobserved heterogeneity, on the other hand is caused by unmeasurable factors such as taste variation of households; social, culture and lifestyle differences and household demographics such as social status. Leszczyc and Bass (1998) indicated four ways by which unobserved heterogeneity can be included in the model (1) heterogeneity can be specified inside or outside the likelihood function, (2) heterogeneity can be modeled using a fixed or a random effects specification, (3) heterogeneity can be included as random intercepts and/or random coefficients, and (4) heterogeneity can be modeled parametrically or non-parametrically.

Omitted heterogeneity can lead to inconsistent model estimates when the differences between individuals/households (*i.e.* heterogeneity) is not adjusted for thereby causing serial correlation in the residuals (see Chamberlain, 1980; Hsiao, 1986 and Diggle *et al*.,1994 for a detailed discussion of heterogeneity bias in discrete-choice models).

3.1.6 Endogeneity of Explanatory Variables

The term ‘endogeneity’ or ‘all effects that are not exogenous’ refers to situations where the observed explanatory variables are correlated with the error components (Louviere *et al.,* 2005). Such situations can occur in vehicle type choice modeling when the observed vehicle attributes are correlated with the unobserved vehicle attributes. Let us consider the choice situation of vehicle make and model by households. The preference for vehicle make and model depends on observed vehicle attributes such as purchase price, engine size, brand loyalty, vehicle dimensions etc. and unobserved vehicle attributes. The error component captures the omitted and unobserved vehicle attributes. It is possible that the purchase price of the vehicle (which is treated as exogenous by most vehicle type choice models) or brand loyalty is correlated with the omitted or unobserved vehicle attributes (for instance, households might prefer owning Ford vehicles due to the goodwill associated with the brand name). This correlation can lead to biased parameter estimates and incorrect inferences. Hence, it is important to capture the possible endogeneity of explanatory variables.

Berry (1994) and Berry *et al.* (1999) used a BLP procedure which corrects for endogeneity of vehicle prices by including alternative-specific constants for each vehicle make and model to estimate the choice model and then regress the estimated constants against vehicle attributes using appropriate instrumental variables. Berry, Levinsohn, and Pakes (1995, 2004), Petrin (2002) and Train and Winston (2004) have used this procedure to correct for the endogeneity of the purchase price in their vehicle choice models. Train and Winston (2004) used an error components model to control for the possible endogeneity of brand loyalty as it is a variant of lagged dependent variable. The aforementioned methods are few of the several methods that have been proposed to correct for endogeneity of explanatory variables (see Louviere *et al.,* 2005 for detailed review of the different forms of endogeneity).

3.2 Factors Influencing Vehicle Holdings and Usage Decisions

The factors influencing vehicle holdings and usage decisions depend on the definition of vehicle type. One of the several ways of defining a vehicle type is based on the body style. Vehicle type, defined by the body style can be classified into (1) Coupe (2) Sedan (3) Hatchback (4) Station Wagon (5) SUV (6) Pickup Truck (7) Minivan (8) Van. Each of these vehicle types has their unique characteristics. For example, Coupes look sporty, but have less room; Sedans make family vehicles; Hatchbacks combine the Sedan roominess with superior luggage capacity; Station Wagons resemble large hatchbacks; SUVs have style along with superior luggage and seat capacity; Pickup trucks carry very heavy loads; Minivan and Vans make spacious vehicles with vans having higher seat capacity than minivans. Though definition of vehicle type by body style is the most conventional way of characterizing it, vehicle type can also be defined based upon (1) vintage *i.e.* the age of the vehicle (2) type of fuel used *i.e.* conventional, methanol or alternative-fuel vehicles; or combinations of these.

In this section, we compile a comprehensive list of all the observed and unobserved factors that influence vehicle type choice and usage decisions, based on the discussion in the previous section. The following sections enumerate each of the factors, and examine them in detail.

3.2.1 Demographic Characteristics

The demographic characteristics of the household such as household income, household size, number of children in the household, presence of a senior adult in the household, household family structure and residential location attributes influence the preferences for different types of vehicles (see, for example, Lave and Train, 1979; Kitamura *et al.,* 2000; Mannering and Mahmassani, 1985, Mohammadian and Miller, 2003b; Train and Winston, 2004; Mannering and Winston, 1985; Train and Lohrer, 1982). For instance, a high-income household would prefer to own SUV while households with more number of children would prefer vehicle types which are spacious such as vans and station wagons (Kitamura *et al.,* 2000).

3.2.2 Individual Characteristics

The individual characteristics such as age, gender, employment status, ethnicity and education influence the preference for different vehicle types across household members. Some studies (see, for example Train, 1986; Golob *et al.* 1997) use the characteristics of the primary driver to better understand the vehicle type choice and usage behavior while other studies (see, for example, Dargay and Vythoulkas, 1999) use the characteristics of the household head (defined as the eldest member of the household). For instance, a vehicle ownership increases with the age of the household head (Dargay and Vythoulkas, 1999).

3.2.3. Household Location Characteristics

The location characteristics of the household such as population density of the zone of residence of the household, zonal employment density, and the zone type of the residential area (central business district (CBD), urban, suburban, or rural), significantly impact the household vehicle holdings and use. For instance, households residing in areas with high population density are less inclined to drive bigger vehicle types such as SUVs and pickup trucks (Bhat and Sen, 2006).

3.2.4 Built Environment Characteristics of Residential Neighborhood

The built environment characteristics of residential neighborhood include land-use structure variables such as percentages and absolute values of residential, commercial/industrial, and other categories, fractions and number of single family and multi-family dwelling units, and fractions and number of households per unit area, and local transportation network measures such as bikeway density (miles of bicycle facility per unit area), street block density (number of street blocks per unit area), accessibility measures, transit availability, and outdoor spaciousness (characterized by lots of off-street parking) to examine vehicle holdings and usage decisions (see, for example, Bhat and Guo, 2006; Cao *et al.*,2006).

3.2.5 Vehicle Attributes

The vehicles types can be classified into a wide range of vehicle makes/models. The vehicle attributes that characterize the makes/models influence the preferences for different makes/models of vehicles (Manski and Sherman, 1980; Mannering and Winston, 1985). These attributes have been discussed in detail below:

1. Purchase Price: The purchase price of the vehicle, used in most of the studies, usually refers to the sticker price of the vehicle with or without taxes and destination charges. The households are less likely to prefer owning and using a vehicle make/model as its price increases. This effect is more pronounced in low-income households than high-income households.
2. Operating Cost: The vehicle operating cost per mile is defined as the price of a gallon of gasoline divided by the vehicle's miles per gallon. The households are less likely to prefer owning and using a vehicle make/model as its operating cost increases.

3. Internal Dimensions – The internal dimensions of the vehicle have been used by most of the studies to model the vehicle make/model choice of the households. They include front headroom space, front legroom space, rear headroom space, rear legroom space, passenger volume, luggage volume, standard payload capacity (for pickup trucks only) and seating capacity. Amongst these vehicle attributes, seating capacity and luggage volume have been found to significantly affect the choice of the vehicle make/model.
4. External Dimensions – The external dimensions of the vehicle can be defined by its wheelbase (distance between the center of the front wheels and the center of the rear wheels), length, height and width. Vehicles with long wheelbases have more interior space which improves the ride. The external dimension variables have been considered in very few studies as they are clearly correlated with internal vehicle dimensions.
5. Vehicle Performance Indicators: The performance of the vehicle can be best judged by the horse power to vehicle weight ratio. Vehicles with more horse power and less weight can give improved performance. As expected, the households prefer vehicles makes/models which have better performance. Other vehicle attributes which are indirect measures of performance are engine size, the number of cylinders and the acceleration time. The more the engine size, the number of cylinders and the acceleration time, the more is the power.
6. Fuel Emissions: The fuel emissions of the vehicle can be adjudged by the type of fuel used by the vehicle (gasoline, diesel or alternative-fuel) and by the amount of

greenhouse gas emissions (tons/year). Alternative-fuel vehicles are considered to be energy efficient vehicles and studies show an increasing preference for alternative-fuel vehicles over the years. Also, the alternative-fuel vehicles emit lesser amount of pollutants than conventional fuel vehicles making them more environment-friendly. Notwithstanding the advantages of alternative-fuel vehicles, the household still prefer conventional vehicles but vehicles which emit lesser amount of pollutants.

7. Type of Drive Wheels: The vehicles have three types of drive wheels – front-wheel-drive, rear-wheel-drive and all-wheel-drive. Front-wheel-drive vehicles have more traction than rear-wheel-drive vehicles and are well-suited for areas with slopes. All-wheel-dive vehicles send the power to both the front and rear, providing better traction in rain, snow and sand.
8. Other Vehicle Attributes: The other vehicle attributes that have been considered by some of the studies to model the choice of vehicle makes/models include transaction search cost, turning radius, crash rating and presence of passenger side airbag. The household seem to prefer vehicle makes/models with less transaction search costs, less turning radius and low crash ratings. As expected, they would prefer vehicle makes/models with a passenger side airbag for safety reasons.

3.2.6 Other Characteristics

Besides the household socio-demographics, individual characteristics and vehicle attributes that influence the preference of households for different types of vehicles, households can also possess intrinsic preferences for certain vehicle types and certain amounts of usage. Most of these characteristics are difficult to measure and may not be perceived by the analyst but are known to the decision-maker. These characteristics are discussed below:

1. Perception of Mobility: Different individuals perceive the amount of their travel differently. An individual A may consider 100 miles a week as a lot of travel while an individual B might consider it otherwise. Based upon their attitude towards mobility, individual A is less likely to prefer to use compact vehicle types (Choo and Mokhtarian, 2004).
2. Enjoyment of Travel: Some individuals might enjoy traveling more than other individuals. Hence, it is reasonable to expect individuals who dislike travel to prefer driving luxury vehicles to make it less unpleasant (Choo and Mokhtarian, 2004).
3. Personality: The personality of individuals, broadly classified into adventure-seeker, organizer, loner and calm personality, can affect his/her preferences for vehicle types and usage (Choo and Mokhtarian, 2004). Individuals who seek adventure would be more willing to prefer SUVs.
4. Lifestyle: The lifestyle factors varies across households depending upon whether the individuals of the household are workaholic, family-oriented, have a high value of time or are status-seeks (Choo and Mokhtarian, 2004). For instance, individuals who give a lot of value to status would be more willing to own luxury vehicles such as large sedans.

5. Attitude towards Driving: Some individuals might consider driving as relaxing experience and enjoy going on long trips while others might consider it stressful and try to keep it minimal (Choo and Mokhtarian, 2004).
6. Perception of Safety: Some individuals might perceive certain vehicle types such as SUVs as safer modes compared to other vehicle types, which thereby influences their vehicle make and usage decision (Cao *et al.,* 2006).
7. Brand Loyalty: Some individuals develop an attitude toward a brand that results from past vehicle ownership experience and cumulative reinforcing information from friends, advertising, and other sources of information. The preferred brand then becomes the standard against which alternatives are judged and it is often observed that these individuals show a strong persistence towards a particular brand. The brand loyalty has been characterized by previous vehicle choice models in different ways: (1) use of dummy variable to indicate whether the new vehicle purchase has the same make as the previous vehicle owned (Manski and Sherman, 1980; Train and Lohrer, 1982) (2) use of vehicle-miles traveled for the make of the model previously owned (Mannering and Winston, 1985) (3) use of number of consecutive purchases of the same brand of vehicle (Mannering and Winston, 1991; Train and Winston, 2004).

The only study that has captured the influence of the first five characteristics on the choice of vehicle types was conducted by Choo and Mokhtarian (2004). This was possible by the use of a survey in which respondents were asked to rate the effect of each of these factors on a five-point semantic-differential scale.

3.3 Conceptual Framework

The conceptual framework presented in this section incorporates all the key issues that form the basis for understanding vehicle holdings and usage decisions (as discussed in section 3.1) and includes all the aforementioned factors that influence the choice decisions (section 3.2).

Figure 1 is an illustration of the conceptual framework. The choice situation can be defined as the joint choice of vehicle types/vintages and usage decisions (upper nest) and the vehicle make/model (lower nest). At the upper nest level, the choice of vehicle types/vintages and usage decisions by the households are influenced by the household demographics (section 3.2.1), individual characteristics (section 3.2.2), household location characteristics (section 3.2.3), built environment characteristics of the residential neighborhood (section 3.2.4), and other characteristics (section 3.2.6). The choice situation is also influenced by satiation effects from owning and using a single vehicle type leading to the choice of multiple vehicle type/vintage alternatives from a set of mutually exclusive alternatives (multiple discreteness). At the lower nest level, the vehicle make/model choice of a household is influenced by the vehicle attributes (section 3.2.5) and brand loyalty in addition to household socio-demographics, individual, characteristics, household location characteristics, and built environment characteristics. The vehicle make/model choice includes the choice of a single make/model alternative from a subset of alternatives (single discreteness).

All these factors influencing the upper and lower nest are considered simultaneously to generate an observed vehicle holdings and usage decision by the households. In addition to these factors, the choice situation is also influenced by unobserved heterogeneity, duration dynamics, state dependence and endogeneity of explanatory variables.

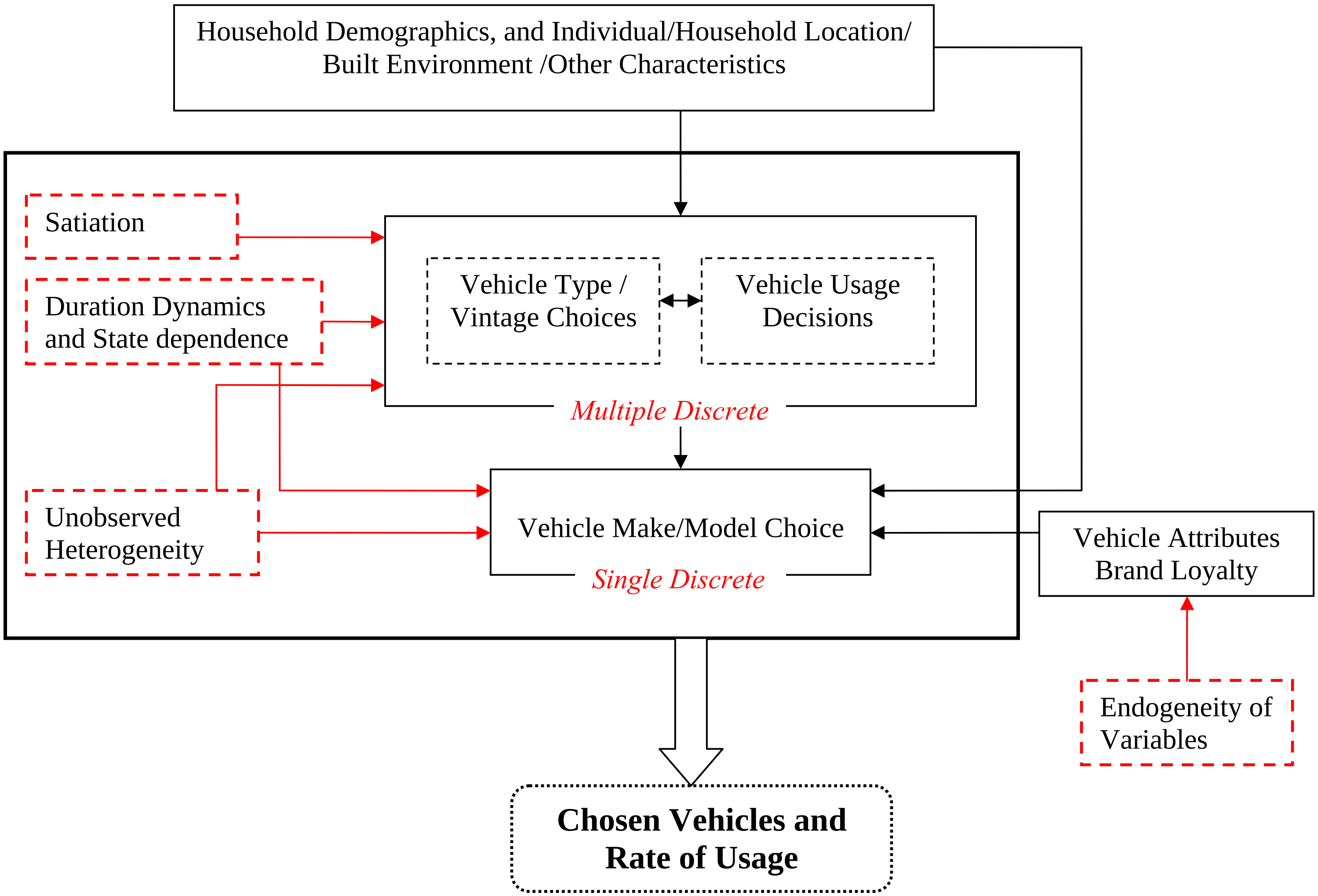

Figure 1. Conceptual Framework for Vehicle Holdings and Usage Decisions

Chapter 4. Modeling Framework

The previous chapter of the dissertation developed a conceptual framework that represents a choice situation characterized by choice of multiple vehicle types/vintages simultaneously (imperfect substitutes) but also the choice of a single vehicle make/model from a subset of alternatives for that particular vehicle type/vintage (perfect substitutes). This chapter translates the conceptual framework and presents a modeling structure based on the random utility theory for Revealed Preference (RP) data which allows for multiple discreteness (choice of multiple alternatives simultaneously) as well as diminishing marginal returns (*i.e.* satiation) from choice of a single vehicle type.[5]

In the following sections, we first formulate the random utility model structure that enables choice of multiple vehicle types/vintages simultaneously (section 4.1) and extend this structure to accommodate choice of perfectly substitutable makes/models of each vehicle type/vintage (section 4.1.1). Next, we present the econometric model for the joint imperfect-perfect good analysis (section 4.2). Finally, we outline the model estimation process (section 4.3). This chapter draws material from the research paper of Bhat *et al.* (2005a).

4.1 Random Utility Model Structure

Let there be K different vehicle type/vintage combinations (for example, old Sedan, new Sedan, old SUV, new SUV etc.) that a household can potentially choose from

[5] It is important to note that we did not accommodate for duration dynamics and state dependence in our modeling framework due to data constraints. Also, the model structure does not capture endogeneity of independent variables.

(for ease in presentation, we will use the term "vehicle type" to refer to vehicle type/vintage combinations). It is important to note that the K vehicle types are imperfect substitutes of each other in that they serve different functional needs of the household. Let m_k be the annual mileage of use for vehicle type k (k = 1, 2,…, K). Also, let the different vehicle types be defined such that households own no more than one vehicle of each type. The utility accrued to a household is specified as the sum of the utilities obtained from using each type of vehicle. Specifically, the utility over the K vehicle types is defined as:

$$U = \sum_{k=1}^{K} \psi(x_k)(m_k + 1)^{\alpha_k} \tag{1}$$

where $\psi(x_k)$ is the baseline utility for using vehicle type k, and α_k are parameters (note that ψ is a function of observed characteristics, x_k, associated with vehicle type k). A translational parameter of 1 is added to m_k for k = 1, 2, 3…, K in the utility function to allow corner solutions (i.e., to allow the possibility that a household does not own one or more vehicle types; see Bhat, 2005 and Kim, 2002). α_k influences the rate of diminishing marginal utility from using a particular vehicle type k. The function in Equation (1) is a valid utility function if $\psi(x_k) > 0$ and $0 < \alpha_k \leq 1$ for all k.

The utility form of Equation (1) is able to accommodate a wide variety of situations characterizing vehicle type preferences based on the values of $\psi(x_k)$ and α_k (k = 1, 2,…, K). A high value of $\psi(x_k)$ for one vehicle type (relative to all other vehicle types), combined with a value of α_k close to 1, implies a high baseline preference and a very low rate of satiation for vehicle type k. This represents the situation when a household primarily uses only one vehicle type for all its travel needs (*i.e.,* a "homogeneity-seeking" household). On the other hand, about equal values of $\psi(x_k)$ and small values of α_k across the various vehicle types *k* represents the situation where the household uses multiple vehicle types to satisfy its travel needs (*i.e.,* a "variety-seeking" household). More generally, the utility form allows a variety of situations characterizing a household's underlying behavioral preferences for different vehicle types, *k*, including (a) low baseline preference and high satiation (low ψ_k and low α_k), (b) high baseline preference and high satiation (high ψ_k and low α_k), (c) low baseline preference and low satiation (low ψ_k and high α_k), and (d) high baseline preference and low satiation (high ψ_k and high α_k).

A statistical model can be developed from the utility structure in Equation (1) by adopting a random utility specification. Specifically, a multiplicative random element is introduced to the baseline utility as follows:

$$\psi(x_k, \varepsilon_k) = \psi(x_k) \cdot e^{\varepsilon_k}, \tag{2}$$

where ε_k captures idiosyncratic (unobserved) characteristics that impact the baseline utility for vehicle type *k*. The exponential form for the introduction of random utility guarantees the positivity of the baseline utility as long as $\psi(x_k) > 0$. To ensure this latter condition, we further parameterize $\psi(x_k)$ as $\exp(\beta' x_k)$, which then leads to the following form for the baseline random utility:

$$\psi(x_k, \varepsilon_k) = \exp(\beta' x_k + \varepsilon_k). \tag{3}$$

The x_k vector in the above equation includes a constant term reflecting the generic preference in the population toward vehicle type *k*. The overall random utility function then takes the following form:

$$\tilde{U} = \sum_{k=1}^{K} [\exp(\beta' x_k + \varepsilon_k)](m_k + 1)^{\alpha_k} \tag{4}$$

From the analyst's perspective, the household is maximizing random utility ($\tilde{U}$) subject to the constraint that $\sum_{k=1}^{K} m_k = M$, where M is the total household annual mileage.

The translated non-linear, but additive, form of the utility function, as stated in Equation 4, allows for multiple discreteness (choice of multiple alternatives simultaneously) as well diminishing marginal returns *(i.e.*, satiation) as the usage of any particular vehicle type increases. This utility function is best suited for choice situations where the alternatives are imperfect substitutes of each other. However, this utility structure does not represent choice situations where consumers choose multiple alternatives at the same time from a certain set of alternatives (*i.e.* imperfectly substitutable alternatives), but also choose only one alternative from among a subset of alternatives (*i.e.* perfectly substitutable alternatives). The extension of the utility function to allow for joint analysis of imperfect and perfect goods is discussed in the next section.

4.1.1 Accommodating Perfectly Substitutable Makes/Models of Each Vehicle Type *k*

Let us consider the case where a vehicle type *k* may be more finely classified into one of several vehicle makes/models. For example, the vehicle type SUV can be one of the several makes/models such as Ford explorer, Jeep Cherokee and Toyota Forerunner.

However, as in the sample used in this dissertation, a household may use only one of the several makes/models of SUV if there is a usage of SUV at all. To handle such situations, partition the discretionary vehicle type *k* into two categories: (1) those that are not more finely classified $(k \notin B)$ and (2) those that are more finely classified $(k \in B)$. Then, we rewrite the utility form of

$$\tilde{\mathrm{U}} = \sum_{k \notin B} [\exp(\beta' x_k + \varepsilon_k)](m_k + 1)^{\alpha_k} + \sum_{k \in B} \left[\exp\left(\max_{l \in N_k} \{W_{lk}\} \right) \right] (m_k + 1)^{\alpha_k}, \tag{5}$$

where the random utility of the make/model *l* of vehicle type *k* is written as:

$$W_{lk} = \beta' x_k + \gamma' z_{lk} + \eta_{kl} \tag{6}$$

In the above expression, $\beta' x_k$ is the overall observed component utility of vehicle type *k*, z_{lk} is an exogenous variable vector influencing the utility of vehicle make/model *l* of vehicle type k $(k \in B)$, γ is a corresponding coefficient vector to be estimated, η_{kl} is an unobserved error component specific to make/model *l* of vehicle type k $(k \in B)$, and N_k is the set of makes/models *l* within vehicle type k $(k \in B)$.

From the analyst's perspective, the household is maximizing random utility $(\tilde{\mathrm{U}})$ subject to the constraint that $\sum_{k=1}^{K} m_k = M$, where M is the total household annual mileage across all the *K* vehicle types. The analyst can then solve for optimal usage by forming the Lagrangian and applying the Kuhn-Tucker conditions. The Lagrangian function for the problem is:

$$\mathcal{L} = \tilde{\mathrm{U}} - \lambda \left[\sum_{k=1}^{K} m_k - M \right], \tag{7}$$

where λ is the Lagrangian multiplier associated with the household annual mileage constraint. The Kuhn-Tucker (K-T) first-order conditions for the optimal usage decisions (the m_k^* values) are given by, (see Bhat *et al.,* 2005a)

$$\left[\exp(\beta' x_k + \varepsilon_k)\right] \ \alpha_k (m_k^* + 1)^{\alpha_k - 1} + \left[\exp\left(\max_{l \in N_k}\{W_{lk}\}\right)\right] \alpha_k (m_k^* + 1)^{\alpha_k - 1} - \lambda = 0\,,$$

$$\text{if } m_k^* > 0\,,\ k = 1, 2, \ldots, K$$

$$\left[\exp(\beta' x_k + \varepsilon_k)\right] \ \alpha_k (m_k^* + 1)^{\alpha_k - 1} + \left[\exp\left(\max_{l \in N_k}\{W_{lk}\}\right)\right] \alpha_k (m_k^* + 1)^{\alpha_k - 1} - \lambda < 0,$$

$$\text{if } m_k^* = 0\,,\ k = 1, 2, \ldots, K \qquad (8)$$

The above conditions have an intuitive interpretation. For all vehicle types which are used (*i.e.*, $m_k^* > 0$), the annual usage is such that the marginal utilities are the same across all vehicles types (and equal to λ) at the optimal usage decision (this is the first set of K-T conditions; note that the sum of the first two term on the left side of the K-T conditions corresponds to marginal utility). Also, for a vehicle type k which is not used, the marginal utility for that vehicle type at zero usage is less than the marginal utility of the other vehicle types that are used (this is the second set of K-T conditions in Equation 8).

The optimal demand satisfies the conditions in Equation (8) plus the usage constraint $\sum_{k=1}^{K} m_k = M$. This constraint implies that the optimal annual miles on only *K-1* vehicle types need to be determined, since the annual miles of use for any one vehicle type can be automatically determined from the annual miles of other vehicle types. The implication is that one of the K vehicle types will have to be considered as the base when introducing a constant or household-specific variables in the utility functions of the K

vehicle types. To accommodate this constraint, designate vehicle type 1 as a vehicle type to which the household allocates some non-zero amount of usage (note that the household should use at least one of the K vehicle types, given that $M > 0$). For the first vehicle type, the Kuhn-Tucker condition may then be written as: (see Bhat *et al.,* 2005a)

$$\lambda = \left[\exp(\beta' x_1 + \varepsilon_1)\right] \ \alpha_1 (m_1^* + 1)^{\alpha_1 - 1} + \left[\exp\left(\max_{l \in N_1}\{W_{l1}\}\right)\right] \alpha_1 (m_1^* + 1)^{\alpha_1 - 1} \qquad (9)$$

Substituting for λ from above into Equation (8) for the other vehicle types (k = 2,…, K), and taking logarithms, we can rewrite the K-T conditions as:

$$\left.\begin{array}{l} H_k = H_1 \ \text{ if } \ \mathrm{m}_k^* > 0 \\ H_k < H_1 \ \text{ if } \ \mathrm{m}_k^* = 0 \end{array}\right\} \ (k = 2, 3, ...K), \qquad (10)$$

where

$$\begin{aligned} H_k &= \beta' x_k + \ln \alpha_k + (\alpha_{kj} - 1)\ln(m_k^* + 1) + \varepsilon_k \ \text{ if k} \notin B, k \geq 1, \\ &= \underset{l \in N_k}{Max}\left\{\beta' x_k + \gamma' z_{lk} + \eta_{kl}\right\} + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) \ \text{ if k} \in B, k \geq 1 \end{aligned} \qquad (11)$$

The satiation parameter, α_k, needs to be bounded between 0 and 1, as discussed earlier. To enforce this condition, we parameterize α_k as $1/[1+\exp(-\delta_k)]$. Further, to allow the satiation parameters to vary across households, we write $\delta_k = \tau_k' y_k$, where y_k is a vector of household characteristics impacting satiation for the kth alternative, and τ_k is a corresponding vector of parameter. Also, note that, in Equation (11), a constant cannot be identified in the $\beta' x_k$ term for one of the K alternatives (because only the difference in H_k from H_1 matters). Similarly, household-specific variables are introduced in the H_k 's for (K-1) alternatives, with the remaining alternative serving as the base (these identification conditions are similar to those in the standard discrete choice model).

4.2 Econometric Model

The assumptions about the ε_k terms $(k \notin B)$, and the η_{kl} terms $(k \in B, l \in N_k)$ complete the econometric specification: different assumptions lead to different model structures. In the remainder of this section, we identify structures with varying levels of flexibility, all of which are also easy to estimate.

4.2.1 Basic Structure

The simplest structure is obtained by assuming that the ε_k terms $(k \notin B)$ and η_{kl} terms $(k \in B)$ are identically standard extreme value distributed. Further, we write the error term η_{kl} as $\eta_{kl} = \lambda_k + \lambda_{kl}$, where λ_k is a common unobserved utility component shared by all vehicle make/model alternatives of vehicle type k (for example, this can characterize unobserved attributes that increase the overall preference for SUV). λ_{kl} is an extreme value term distributed identically with scale parameter θ_k $(0 < \theta_k \leq 1 \ \forall \ k \in B)$. The λ_{kl} terms are independent of one another and of the λ_k and ε_k terms.

With the above assumptions and using the properties of the extreme value distribution, we can simplify the expression for H_k for $k \in B$ as:

$$
\begin{aligned}
H_k &= \beta' x_k + \lambda_k + \underset{l \in N_k}{Max}\{\gamma' z_{lk} + \lambda_{kl}\} + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) \\
&= \beta' x_k + \theta_k \ln \sum_{l \in N_k} \exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right) + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) + \varepsilon_k \ ,
\end{aligned} \tag{12}
$$

where ε_k $(k \in B)$ is also now standard extreme value distributed. Then, following the derivation of the Multiple Discrete Continuous Extreme Value (MDCEV) model in Bhat (2005), the marginal probability that the household uses first Q of the *K* vehicle types (Q ≥ 1) for annual mileages $m_1^*, m_2^*, ...m_Q^*$ may be written as:

$$
P(m_1^*, m_2^*, ...m_Q^*, 0, 0, 0, ..., 0) = \left[\prod_{k=1}^{Q} r_k\right]\left[\sum_{k=1}^{Q} \frac{1}{r_k}\right]\left[\frac{\prod_{k=1}^{Q} e^{V_k}}{\left(\sum_{h=1}^{K} e^{V_h}\right)^Q}\right](Q-1)!, \tag{13}
$$

where

$$
\begin{aligned}
r_k &= \left(\frac{1-\alpha_k}{m_k^* + 1}\right) \ \textit{and} \\
V_k &= \beta' x_k + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1) \text{ if } k \notin B, k \geq 1, \\
&= \beta' x_k + \theta_k \ln \sum_{l \in N_k} \exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right) + \ln \alpha_k + (\alpha_k - 1)\ln(m_k^* + 1), \text{ if } k \in B, k \geq 1
\end{aligned} \tag{14}
$$

The conditional probability that vehicle make/model *l* will be used for an annual mileage $m_k^* (l \in N_k, k \in B)$, given that $m_k^* > 0$, may be obtained from Equation (6) as:

$$
P(l \mid m_k^* > 0;\ l \in N_k) = \frac{\exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right)}{\sum_{g \in N_k} \exp\left(\frac{\gamma' z_{gk}}{\theta_k}\right)} \tag{15}
$$

Next, let k = 1,2, 3, …S ($S \leq$ Q-1) be the vehicle types used by the household that are more finely classified into vehicle makes/models, while vehicle types k = S+1, S+2,…Q are the ones that the household uses in that are not further categorized into vehicle makes/models. Then, the unconditional probability that the household uses vehicle make/model *a* of vehicle type 1 for annual mileage m^*_{1a}, make/model *b* of vehicle type 2 for m^*_{2b}, … make/model *s* of vehicle type *S* for m^*_{Ss}, , and for annual mileages $m^*_{S+1}, m^*_{S+2} ... m^*_Q$ in the other vehicle types may be written as

$$\begin{aligned} &P(m^*_{1a}, m^*_{2b}, m^*_{3c}, ... m^*_{Ss}, m^*_{S+1}, m^*_{S+2} ... m^*_Q, 0, 0 ... 0) \\ &= P(m^*_1, m^*_2, ... m^*_Q, 0, 0, ... 0) \times P(a \mid m^*_1 > 0) \times P(b \mid m^*_2 > 0) ... P(s \mid m^*_S > 0) \end{aligned} \tag{16}$$

There are two points to note in the expression above. First, the parameters γ and $\theta_k (k \in B)$ appear in both the MDCEV probability expression $P(m^*_1, m^*_2, ... m^*_Q, 0, 0, 0, ..., 0)$ as well as the standard discrete choice probability expression for the choice of make/model of vehicle type *k* that is more finely classified into many makes/models. This creates the jointness in the multiple discrete and single discrete choices. Second, if $\theta_k = 1$ for all $k \in B$, the joint model collapses to a restricted version of the MDCEV model with a total number of $K + \sum_{k \in B} G_k$ alternatives, where G_k is the number of alternatives in N_k. This can be easily observed from Equation (13) and Equation (15) by noting that the $\sum_{l \in N_k} \exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right)$ terms in the denominators of the single discrete choice models for vehicle makes/models of each (and all) vehicle type $k \in B$ cancel with identical terms occurring in the $\prod_{k=1}^{Q} e^{V_k}$ expression in the MDCEV probability expression of Equation (13). The restriction in the resulting MDCEV model is that the satiation parameter is equal across those “new” alternatives in the expanded choice set that are vehicle makes/models within the alternatives in the original MDCEV model. This restriction is to be expected, because different satiation parameters for the vehicle make/model alternatives would imply "imperfect" substitution, which cannot be allowed since only one make/model is chosen within each vehicle type.

4.2.2 Mixed Joint Model

The model developed thus far does not incorporate error correlation and/or random components in either the MDCEV vehicle type component or in the MNL make/model component. These can be accommodated by considering the β vector in the baseline preference of the MDCEV component and the γ vector characterizing the parameters in the MNL models as being draws from multivariate normal distributions $\phi(\beta)$ and $\phi(\gamma)$. The unconditional probability of vehicle holdings and usage may then be written as:

$$
\begin{aligned}
&P(m_{1a}^*, m_{2b}^*, m_{3c}^*, \ldots m_{Qq}^*, 0, 0, 0, \ldots 0) \\
&= \int_{\beta}\int_{\gamma} \Big\{ P(m_1^*, m_2^*, \ldots m_Q^*, 0, 0, \ldots 0) \times P(a \mid m_1^* > 0) \times P(b \mid m_2^* > 0) \\
&\qquad\qquad \ldots \times P(q \mid m_Q^* > 0) \mid (\beta, \gamma) \Big\} \phi(\beta)\phi(\gamma)\, \mathrm{d}\beta\, \mathrm{d}\gamma
\end{aligned}
\tag{17}
$$

4.3 Model Estimation

The mixed joint model can be estimated in a straight-forward manner using the maximum simulated likelihood approach. The likelihood function for any particular household is given by (17). We use Halton draws in the current research (see Bhat, 2003). The parameters to be estimated in the model structure include the moment parameters characterizing the β and the γ multivariate distributions, the τ_k vector for each alternative *k* (embedded in the scalar α_k within V_k), and the θ_k scalars for each alternative *k*.

4.4 Summary

This chapter presented detailed econometric structures for analyzing the vehicle holdings and usage decisions. Specifically, we used a multinomial logit structure to analyze the choice of a single make and model within each vehicle type/vintage chosen, and nested this MNL structure within an MDCEV formulation to analyze the simultaneous choice of multiple vehicle types/vintages and usage decisions. This joint MDCEV-MNL model was further extended to include random coefficients/error components in the MDCEV component and MNL component. The likelihood function and the analytical gradient for the joint MDCEV-MNL model were coded in the GAUSS 7.0 (Aptech Systems, Inc.) programming language. The maximum likelihood estimation was performed using the MAXLIK library of functions.

Chapter 5. Data

This chapter describes the Revealed Preference (RP) data used in the empirical estimation. The data sources are first presented (section 5.1). The sample formation process is then discussed (section 5.2). Finally, some sample characteristics are presented (section 5.3).

5.1 Data Sources

The primary data source used for this analysis is the 2000 San Francisco Bay Area Travel Survey (BATS). This survey was designed and administered by MORPACE International Inc. for the Bay Area Metropolitan Transportation Commission. The survey collected information on vehicle fleet mix of over 15,000 households in the Bay Area for a two-day period (see MORPACE International Inc., 2002 for details on survey, sampling, and administration procedures). The information collected on household vehicle ownership included the make/model of all the vehicles owned by the household, the year of possession of the vehicles, odometer reading on the day of their possession, the year of manufacture of each vehicle, and the odometer reading of each vehicle on the two days of the survey. Furthermore, data on individual and household demographics, and activity travel characteristics, were collected.

In addition to the 2000 BATS data, several other secondary sources were used to generate the dataset in the current analysis. Specifically, data on purchase price (for new and used vehicles), engine size (in liters) and cylinders, engine horse power, vehicle weight, wheelbase, length, width, height, front/rear head room and leg room space, seating capacity, luggage volume, passenger volume and standard payload (for pickup trucks only) were obtained for each vehicle make/model from *Consumer Guides* (Consumer Guide, 2005). Data on annual fuel cost, fuel type (gasoline, diesel), type of drive wheels (front-wheel, rear-wheel and all-wheel) and annual greenhouse gas emissions (in tons) were obtained from the *EPA Fuel Economy Guide* (EPA, 2005). Residential location variables and built environment attributes were constructed from land use/demographic coverage data, a GIS layer of bicycle facilities, and the Census 2000 Tiger files (the first two datasets were obtained from the Metropolitan Transportation Commission of the San Francisco Bay area).

5.2 Sample Formation

The BATS survey data is available in four files: (1) vehicle file (2) person file (3) activity file and (4) household file. The vehicle file provides information on the characteristics of all the vehicles owned by the household such as make/model of all the vehicles owned by the household, mileage and vintage of each of the vehicles. The person file has information on the demographic characteristics of the survey respondents (gender, age, ethnicity, employment status, etc.). The activity file provides detailed characteristics (activity type, start and end times, etc.) of each of the activity episodes undertaken by the survey respondents. The household file includes information on the socio-demographic characteristics of the households that responded to the survey such as household income, household size, number of children and family structure. Each of these files was screened for missing or inconsistent data.

The first step in the sample formation process was to categorize the vehicles in the vehicle file into one of 20 vehicle classes, based upon vehicle type and vintage. In addition to providing a good characterization of vehicle type/vintage, the classification scheme adopted was also based on ensuring that no household owned more than 1 vehicle of each vehicle type/vintage. This ensures that the model provides a comprehensive characterization of all dimensions corresponding to vehicle holdings and usage. The ten vehicle types used were (1) Coupe (2) Subcompact Sedan (3) Compact Sedan (4) Mid-size Sedan (5) Large Sedan (6) Hatchback/Station Wagon (which we will refer to as Station Wagons for brevity) (7) Sports Utility Vehicle (SUV) (8) Pickup Truck (9) Minivan and (10) Van. The two categories for vintage of each of these vehicle types were (1) New vehicles (2) Old Vehicles. A vehicle was defined as 'new' if the age of the vehicle (survey year minus the year of manufacture) was less than or equal to 5 years, and 'old' if the age of the vehicle was more than 5 years.

Within each of the 20 vehicle type/vintage classes, there are a large number of makes/models. For practical reasons, we collapsed the makes/models into commonly held distinct makes/models and grouped the other makes/models into a single "other" make/model category.[6] Figure 2 indicates the broad classification of vehicles into vehicle type/vintage categories and make/model subcategories. After classifying the vehicles, the vehicle dataset was populated with information on vehicle attributes obtained from secondary data sources. For those vehicle makes/models which belonged to the 'other' category, an average value of the vehicle attributes of all the vehicle makes/models which

[6] A vehicle make/model was defined as not being "commonly held" if less than 1% of the vehicles in the vehicle type/vintage category were of that make/model.

belonged to that vehicle type/vintage category was used. The annual mileage[7] for each vehicle was then computed.

The person file data was next screened to obtain information on the socio-demographic characteristics of the household head, including age, ethnicity, gender, and employment status.[8] Subsequently, the activity file was used to obtain information on the usage of non-motorized forms of transportation by the household members. The duration spent in walking and biking on the two days of the survey were aggregated across all the household members and projected to an annual level. Based upon the average rate of walking (3.5 miles/hour) and biking (15 miles/hour), the annual usage (miles) of non-motorized forms of transportation of a household was obtained.

After preparing the data from the vehicle, person and activity files, as discussed above, the resulting dataset was appended to the household file. The built environment variables were also added at this stage based on household location. The final sample comprised 8107 records that represented households that own at least one vehicle.[9]

5.3 Descriptive Statistics

Table 1 shows the distribution of the vehicles owned by the households. Most of the households (55%) own one vehicle, 36% own two-vehicles and the rest own three or

---

[7] Annual Mileage = (mileage recorded by odometer on second survey day – miles on possession)/ (survey year – year of possession)

[8] The household head was defined as the employed individual in one-worker household. If all the adults in a household were unemployed, or if more than 1 adult was employed, the oldest member was defined as the household head.

[9] Our framework enables the modeling of the decision to not own vehicles too. Such households will exclusively use non-motorized forms of personal mode of travel. However, due to the very small percentage of households in the Bay Area owning no vehicles (<5%), and the substantial presence of missing information on the potential determinants of vehicle holdings and use in these households, the final sample included only households that own one or more vehicles.

more vehicles. Table 2 shows the descriptive statistics of usage of different vehicle types/vintages owned by households. The second and the third columns of the table indicate the frequency (percentage) of the households owning vehicle type/vintage category and the annual usage of the vehicle by the households owning that vehicle type/vintage, respectively. The observations made from the statistics in these two columns are as follows. First, most of the households own old midsize sedans (19% of the households), old pickup trucks (15% of the households) and old compact sedans (14% of the households), making them the most commonly owned vehicle types/vintages by households. Also, these vehicle types/vintages have a high annual usage (as observed in the third column of Table 2). This suggests a high baseline utility preference and low satiation for old midsize sedans, old pickup trucks and old compact sedans. Second, other most commonly owned vehicle types/vintages include old coupes (13% of the households) and new midsize sedans (12% of the households). Interestingly, these two vehicle types/vintages are also amongst the motorized vehicles with the least annual mileage. This indicates a high baseline preference, and a high satiation in the use of old coupes and new midsize sedans. Third, a small percentage of households own vehicle types/vintages with very high annual usage such as new van, new and old minivan, old SUV and old subcompact sedans. This reflects a low baseline preference and low satiation for these vehicle types/vintages. Fourth, new vans and old vans have the lowest baseline preference, and the new large sedan category has a high satiation effect (*i.e.* lowest annual usage) amongst all motorized vehicle types/vintages. Fifth, only 3% of the households use non-motorized forms of transportation (as observed in the last row of

Table 2). Also, as expected, the non-motorized form of transportation has the least annual miles amongst all the vehicle types/vintages.

The last two columns in Table 2 indicate the split between one-vehicle households (*i.e.*, households that own and use one vehicle type or a corner solution) and multiple vehicle households (i.e., households that own and use multiple vehicle types or interior solutions) for each vehicle type/vintage category. Thus, the number for new coupe indicates that, of the 389 households that own a new coupe, 132 (34%) own a new coupe only and 257 (66%) own new coupe along with one or more vehicle types/vintages. The statistics for one-vehicle households (as observed in the fourth column) show that old and new subcompact sedans, and old and new compact sedans, are the most commonly owned vehicles by such households, while new vans are the least commonly owned vehicle type/vintage. The results further indicate that households owning and using new vans, new minivans, new pickup trucks and old pickup trucks are most likely two and more vehicle households. Additionally, households always use the non-motorized form of transportation in combination with motorized vehicle types/vintages (as observed in the last row in Table 2).

Table 3 shows the descriptive statistics for two-vehicle households. The second column indicates the frequency (percentage) of two-vehicle households owning the vehicle type/vintage category listed in the first column (Vehicle 1) as one of the two vehicle type/vintages. The statistics indicate that most of the two-vehicle households own old midsize sedans (23% of the households), old pickup truck (20% of the households) and old compact sedans (18% of the households). The third column indicates the most popular combination of Vehicle 1 with the vehicle type/vintage of the second vehicle.

Thus, for example, households owning new coupe are most likely to also own old pickup trucks (13% = 23/182 of two-vehicle households owning new coupes also own old pickup trucks).

5.4 Summary

The primary source of data used for estimation is drawn from 2000 BATS. In addition, supplementary data on vehicle make/model attributes, residential location variables and built environment attributes is also used. The final sample was obtained after subjecting the data to substantial processing. Details of this sample formation process were presented in this chapter. Further, the chapter also provides detailed sample characteristics.

Chapter 6. Empirical Results

This chapter presents the empirical results of the joint MDCEV-MNL model for examining the vehicle type/vintage, make/model and usage decisions of the household. The model was estimated at different numbers of Halton draws per observation. However, there was literally no change in the estimation results beyond 50 Halton draws per observation (this is related to the large number of observations available for estimation). In our estimations, we used 100 Halton draws per observation.

The effects of the exogenous variables at the multiple discrete-continuous level are presented first (section 6.1.1), followed by effects of exogenous variables at the single discrete choice level (section 6.1.2). This is followed by effects of satiation (section 6.2), effects of logsum parameters (section 6.3), overall likelihood-based measures of fit (section 6.4) and application of the model (section 6.5).

6.1 Variable Effects

The effects of exogenous variables at the multiple discrete-continuous level and at the single discrete choice level are estimated jointly, along with the satiation parameters at the multiple discrete-continuous level, and the logsum parameters (*i.e.*, the θ_k parameters). In this section, we discuss the variable effects separately in the multiple discrete-continuous level and at the simple discrete-choice level for ease in presentation. It is important to note that the variables in the single discrete choice model affect the baseline utility of the corresponding multiple discrete-continuous alternative through the logsum variable, $\ln \sum_{k \in N_k} \exp\left(\frac{\gamma' z_{lk}}{\theta_k}\right)$.

6.1.1 MDCEV Model

The final specification results of the MDCEV component of the vehicle holdings and usage model are presented in Table 4 (the results corresponding to any given variable span two pages, because there are 21 vehicle type/vintage categories; each column of Table 4 represents one vehicle type/vintage). The vehicle type/vintage category of "new coupe" serves as the base category for all variables (and, thus, this vehicle type/vintage does not appear in the table as a column). In addition, a "-" entry corresponding to a variable for any vehicle type/vintage category implies that the category also constitutes the base category for the variable.

6.1.1.1 Household Demographics

The household demographic variables considered for the model include household income, categorized into low-income (less than \$35,000), medium-income (between \$35,000 and \$90,000) and high-income households (greater than \$90,000). Other variables include presence of children in the household, presence of senior adults in the household, household size and number of employed people in the household.

Household Income

The household income effects indicate that medium and high income households have a high preference, relative to low income households, for new SUVs (see, Kitamura *et al.,* 2000 and Choo and Mokhtarian, 2004 for similar results), and a low preference for old vans (see the positive coefficients in the “new SUV” column and the negative coefficients in the “old van” column corresponding to the medium and high annual income rows of the table). Medium (high) income households also have a higher (lower) baseline preference for old pickup truck, old minivan, and old station wagons relative to low income households. Overall, the high income households have a lower baseline preference for older vehicles relative to low/middle income households, consistent with the ownership and usage of new vehicles by high income households (see the negative coefficients corresponding to the old vintage categories in the row for the high income dummy variable). Interestingly, high income households are also less likely than low and middle income households to undertake activities using non-motorized forms of transportation (see last column of the table corresponding to the high annual income row of the table.

Presence of Children in the Household

The presence of children in the household has a substantial effect on vehicle type/vintage choice and use as indicated by the model results. The variables used for examining this effect include presence of children less than 4 years of age, presence of children between 5 and 15 years of age and presence of children between 16 and 17 years of age.

The results show that households with very small children (less than or equal to 4 years of age) are more likely to use compact sedans, mid-size sedans, and SUVs than other households. In addition, the coefficients under the columns “new minivan” and ‘old minivan” for “presence of children less than or equal to 4 years” and “presence of children between 5 and 15 years” suggest that households with children prefer minivans, presumably due to the spacious, affordable, and family oriented nature of minivans.

Also, the results show that households with children between 16 and 17 years of age are unlikely to own/use old vans. This result is intuitive, since 16 or 17 years old adolescents are eligible to drive and are more likely to prefer owning/using vehicles types that are sporty and stylish.

Presence of Senior Adults in the Household

Households with senior adults (greater than 65 years) are more likely to own and use compact, mid-size, and large sedans relative to coupes and subcompact sedans. This is perhaps due to the preference for vehicles that are easy to get in and out of. Households with senior adults are also more likely to own old station wagons and old vans, as well as travel more by non-motorized forms of transportation compared to other households.

Household Size

The household size coefficients are positive for the vehicle types corresponding to mid-size sedans, large sedans, station wagons, SUVs, pickup trucks, minivans and vans. This suggests a preference for bigger vehicles (to carry more people) rather than the smaller vehicle types of coupes, subcompact sedans, and compact sedans. It is also interesting to note that households with more members, in general, prefer older vehicle types than newer vehicle types. This may be because of less discretionary income of such households, leading them to invest in more affordable vehicles that meet their functional needs.

Number of Employed People in the Household

Household with more number of employed members have a high baseline preference for new vehicle types such as subcompact sedans and compact sedans, and an overall low baseline preference for large sedans and minivans. These results clearly indicate that households with several employed members prefer vehicle types that are new and compact rather than vehicle types that are old and have high seating capacity. Also, the results show that these households use non-motorized forms of transportation (such as walking and biking) less than other households.

6.1.1.2 Household Location Characteristics

The household location variables considered for the model includes location of the household in central business district, urban zone, suburban zone and rural zone. Other variables considered include population density and employment density.

The household location attribute effects indicate that households in suburban zones are, in general, less likely to own and use old vehicles relative to households in urban zones. Suburban and rural households are also more likely to own pickup trucks relative to urban households (see the positive coefficients corresponding to the new pickup and old pickup truck columns corresponding to the suburban and rural rows of

Table 4). This latter result, consistent with Cao et al. (2006), is presumably because of the rugged terrains of suburban/rural areas and the occupational/family needs of suburban/rural households. This impact is further emphasized by the negative effect of employment density on the holding and use of new pickup trucks.

6.1.1.3 Built Environment Characteristics of the Residential Neighborhood

The built environment variables corresponding to a household's residential neighborhood included land-use structure variables and local transportation network measures. The land-use structure variables include the percentages and absolute values of residential, commercial/industrial, and other categories, fractions and number of single family and multi-family dwelling units, and fractions and number of households living in single family and multi-family dwelling units. The local transportation network measures include bikeway density (miles of bicycle facility per unit area), street block density (number of street blocks per unit area), highway density (miles of highway per unit area), and local road density (miles of local road per unit area). All the built environment variables are computed at the zonal level as well as for 0.25 mile, 1 mile, and around the residence of each household[10].

The built environment characteristics of the household neighborhood indicate that households located in highly residential areas are less likely to prefer large vehicle types such as pickup trucks and vans, irrespective of the age of the vehicle. A similar result is observed for households located in neighborhoods with high commercial/industrial acres.

[10] An implicit assumption in using the built environment variables as exogenous determinants of vehicle holdings and use decisions is that residential location choice and vehicle-related decisions are not jointly made. Bhat and Guo (2006) propose a framework to accommodate such residential sorting effects. However, this issue is beyond the scope of this dissertation.

These results are intuitive, because neighborhoods with dense residential or commercial areas have space constraints for parking and maneuvering, leading to a preference for compact vehicles. Also, the results indicate the low baseline preference of households located in a neighborhood with high multi-family dwelling units for large sedans. This result is not immediately intuitive and needs additional exploration in future studies.

The results further indicate that households located in a neighborhood with high bike lane density have a high baseline preference for non-motorized modes of transportation, presumably because such neighborhoods encourage walking and bicycling. Also, households located in a neighborhood with high street block density are more likely to prefer smaller vehicle types (such as subcompact and compact sedans), and older vehicles, relative to new vehicles.

6.1.1.4 Characteristics of the Household Head

The characteristics of the Household Head (HH) considered in the model include age (classified into less than 30 years of age, 31 to 45 years of age and greater than 45 years of age), gender and ethnicity (primarily, Caucasian, African-American, Hispanic, Asian and Other).

The impacts of the household head characteristics suggest that older households (i.e., households whose heads are greater than 30 years) are generally more likely to own vehicles of an older vintage compared to younger households (i.e., households whose heads are less than or equal to 30 years of age). This can be inferred from the negative signs on the age-related dummy variables for the new vehicle types, and the positive signs on the age-related dummy variables for the old vehicle types, in Table 4. In addition, older households are more likely to own minivans and old vans, and travel by non-motorized forms of transportation.

The “male” variable effects point to a higher baseline preference for older and larger vehicles if the male is the oldest member (or only adult) in the household relative to households with the female being the oldest member (or only adult). Finally, the ethnicity variables are also highly significant, with Asians more likely to own sedans and new minivans, and less likely to own pickup trucks, compared to other ethnicities. These and other ethnicity effects, may reflect overall cultural differences in preferences, and need to be examined more extensively in future studies.

6.1.1.5 Baseline Preference Constants

The baseline preference constants do not have any substantive interpretation, and are included to accommodate generic differences in preference across the vehicle types/vintages and the range of independent variables used in the model.

6.1.1.6 Random Error Components/ Coefficients

Several different specifications for random error components and random coefficients were attempted in the MDCEV component of the joint model. The preferred specification included two error components as follows: (1) Coupes (standard deviation of 0.394 with a t-statistic of 2.08) and (2) old vehicles (standard deviation of 0.517 with a t-statistic of 7.73). The error component corresponding to coupes provides evidence that households preferring old coupes due to unobserved factors (such as, for example, an inclination for sporty, small vehicles) also prefer new coupes. Similarly, there may be tangible unobserved factors, such as a generic dislike for the “old” label, that may decrease the utility of all old vehicles.

6.1.2 MNL Model for Vehicle Make/Model Choice

Table 5 provides the results for the Multinomial Logit (MNL) model for the choice of vehicle make/model by the households, conditional on choice of a vehicle type/vintage category. The variables considered for examining the choice of vehicle make/model include household demographic characteristics and vehicle attributes primarily purchase price, fuel cost, seating capacity, luggage volume, engine size, number of cylinders, front headroom space, front legroom space, rear headroom space, rear legroom space, standard payload capacity (for pickup trucks only), wheelbase, length, height, width, horse power, vehicle weight, type of fuel used, amount of greenhouse gas emissions (tons/year), types of drive wheels and type of vehicle make. All the variables are introduced with generic parameters, with the coefficients of the variables held to be the same value across all the MNL logit models for the different vehicle type/vintage categories.

6.1.2.1 Cost Variables

The effects of the cost variables are intuitive: Households, on average, prefer vehicle makes and models that are less expensive to purchase and operate. As expected, households with high incomes are less sensitive to cost variables than are households with low incomes (see, Lave and Train, 1979, Mannering and Winston, 1985, for similar results). Also, the standard deviation of the random coefficient corresponding to purchase price/income is highly statistically significant, indicating the presence of unobserved heterogeneity across households to purchase price. A comparison of the mean and standard deviation of this coefficient shows that less than 1% of the households positively value purchase price. However, we found no unobserved heterogeneity to fuel cost. Finally, it is interesting to note the lower sensitivity to fuel cost relative to purchase price. This is understandable, since the purchase price constitutes a large investment at one point in time, while the annual fuel cost is incurred over multiple gas station trips.

6.1.2.2 Internal Dimensions

Households with 2 or less members are less likely, compared to households with more than 2 members, to prefer vehicle makes/models with high seat capacity. This is intuitive because of the need to be able to carry more individuals. Also, households prefer vehicle makes/models with high luggage volume and high standard payload capacity (the latter is applicable to pickup trucks only). This is presumably because households prefer vehicles with superior luggage volume so that they can make long recreational trips. In the case of pickup trucks, households prefer vehicle makes/models that have high standard payload capacity so that it can haul heavier luggage.

6.1.2.3 Vehicle Performance Indicators

The performance of the vehicle make/model was captured by using horse power to vehicle weight ratio. This ratio was used because vehicles with more horse power and less vehicle weight give an improved performance. The results indicate that households have a strong baseline preference for vehicle makes/models with powerful and efficient engines. An indirect measure of vehicle performance considered in this model is the engine size. The households prefer vehicle makes/models with less engine size. This might be because engines with greater capacities consume more fuel though they are usually more powerful and provide greater torque at lower rpms (rotations per minute).

6.1.2.4 Type of Drive Wheels and Vehicle Make

Households in the San Francisco Bay area are less likely to prefer vehicle makes/models with all-wheel-drive than vehicles with rear-wheel drive. This might be because households do not require that much power in both the front and rear wheels provided by all-wheel-drive vehicles for their daily commute. Further, households prefer makes/models associated with Ford, Honda, Toyota, Cadillac, Volkswagen and Dodge relative to makes/models of other car manufacturers.

6.1.2.5 Fuel Emissions and Type

Households are less likely to use vehicle makes/models with high amounts of greenhouse gas emissions, perhaps because of the detrimental environmental and health impacts of harmful tailpipe emissions. Further, the results indicate that households are less likely to prefer vehicle makes/models that require premium gasoline compared to vehicle makes/models that can operate on regular or premium gasoline.

6.1.2.6 Trade-off Analysis

A trade-off analysis was conducted to assess the household’s willingness to pay for an additional unit of vehicle attribute. The average household income of the sample was considered for the analysis. The results indicate that the households significantly value additional units of luggage volume and vehicle performance. The household with an average income of $82,240 is willing to pay an additional purchase price of $109 for an additional cubic of luggage volume and $164 for additional Horsepower for a vehicle with an average weight of 3185 pounds. Additionally, the results indicate that such households are also willing to pay $2039 for a reduction in the green house gas emissions of 1 ton per year. This latter result clearly indicates a strong inclination of such households towards vehicle makes/models that are environment friendly.

6.2 Satiation Effects

The satiation parameter, α_k, for each vehicle type k is parameterized as $1/[1+\exp(-\delta_k)]$, where $\delta_k = \tau_k' y_k$, where y_k is a vector of household characteristics impacting satiation for the k^{th} vehicle type/vintage alternative. This parameterization allows α_k to vary across households and still be bounded between 0 and 1.

The estimated values of α_k and the t-statistics with respect to the null hypothesis of α_k =1 (note that standard discrete choice models assume α_k =1) are presented in Table 6. The table indicates the following results. <u>First</u>, all the satiation parameters are very significantly different from 1, thereby rejecting the linear utility structure employed in standard discrete choice models. That is, there are clear satiation effects in vehicle holdings and usage decisions. Second, as expected, middle and high income households are more likely to get satiated with the increasing use of any vehicle type/vintage compared to low income households. That is, middle and high income households are more likely to own and use multiple types/vintages of vehicles. Third, low income households are least likely to get satiated with the increasing use of old subcompact sedans, new and old compact sedans, and old midsize sedans, presumably because these vehicle type/vintage categories efficiently satisfy the functional needs of such households. Finally, the satiation effect is highest for non-motorized mode of transportation compared to all vehicle type/vintage categories. This is to be expected since the annual miles of walking and bicycling is very small relative to the use of motorized vehicles.

6.3 Logsum Parameters

The logsum parameters (*i.e.* θ_k parameters) create jointness between the single discrete choice component and the MDCEV components of the MDCEV-MNL model. There are two logsum parameters: (1) The logsum parameter for the makes/models corresponding to the old SUV, old minivan, new minivan, old van, and new van vehicle type/vintage categories is estimated to be 0.5354 (the t-statistic for the test that the parameter is different from 1 is 4.61), (2) The logsum parameter for the rest of the vehicle type/vintages is estimated to be 0.8378 (the t-statistic for the test that the parameter is different from 1 is 1.05). The logsum parameters indicate the presence of common unobserved attributes that affect the utilities of all makes/models corresponding to a given vehicle type/vintage category.

6.4 Overall Likelihood-Based Measures of Fit

The log-likelihood value at convergence of the final joint model is -87215. The corresponding value for the model with only the constants in the MDCEV and single discrete choice components, the satiation parameters, and unit logsum parameters is -90264. The likelihood ratio test for testing the presence of exogenous variable effects, satiation effects, and logsum effects is 6098, which is substantially larger than the critical chi-square value with 192 degrees of freedom at any reasonable level of significance. This clearly indicates the value of the model estimated in this paper to predict vehicle holdings and usage.

6.5 Application of the Model

The model estimated in this dissertation can be used to determine the change in the holdings and usage of vehicle types due to changes in independent variables. To do so at the mean parameter value on purchase price, we compute the logsum variable from the MNL models and predict vehicle holdings and usage by maximizing the systematic part of the random utility expression of Equation (4) (after including the computed logsum variable) under the constraint that $\sum_k m_k = M$.

In this section, we demonstrate the application of the model by studying the effect of an increase in bike lane density, an increase in the street block density, and an increase in the vehicle fuel cost. Specifically, we increase the length of bikeways within a 0.25 mile radius of household's residences by 25%, increase the number of street blocks within 1 mile radius of household's residences by 25%, and increase the fuel cost by 25%. These changes are applied to each household in the sample. To examine the impact of these changes, we computed the predicted aggregate vehicle holdings and use patterns before and after the changes, and obtained a percentage change from the baseline estimates. The effect of the changes on aggregate vehicle holdings and use patterns is measured along two dimensions: (1) Percentage change in the number of households owning a particular vehicle type, and (2) Net percentage change in the annual miles of usage of each vehicle type. The vehicle types/vintages have been regrouped into six categories to better understand the implication of these changes. They are (1) Compact cars including new and old coupes, subcompact sedans, compact sedans and station wagons (2) new and old Midsize and large sedans (3) new and old SUVs (4) new and old Pickup trucks (5) new and old Minivans and Vans, and (6) Non-motorized modes of transportation. Table 7 presents the results for a 25% increase in the bike lane density, a 25% increase in the street block density, and a 25% increase in fuel cost. A “-“ entry in the table indicates changes less than 0.2% along both the dimensions of holdings and usage.

The results from Table 7 indicate that an increase in bike lane density results in a marginal decrease in the holdings as well as usage of all motorized vehicle types. Further, as expected, the results indicate a significant increase in the use, and intensity of use, of non-motorized modes of transportation. Thus, the results show that an increase in the bike lane density discourages the ownership and use of all motorized vehicle types.

An increase in street block density results in a significant increase in the holdings of compact cars and a mild decrease in the holdings of pickup trucks. Further, the results indicate a high positive increase in the usage of compact cars and a marginal decrease in the use of other motorized vehicle types. The overall significant increase in the holdings and usage of compact cars indicates that increasing street block density encourages the use of small vehicles which are easy to maneuver. As expected, the holdings and usage of non-compact cars decrease with increasing number of street blocks. Additionally, the results show a significant decrease in the holdings and the use of non-motorized modes of transportation. This result is intuitive, because additional traffic contributed by the increase in the number of street blocks leads to safety concerns and thereby, hinders the use of non-motorized modes of transportation (see, Stinson and Bhat, 2004 for similar results).

Finally, an increase in the fuel cost leads to a marginal increase in the holdings of compact cars and a significant decrease in the holdings of pickup trucks, minivans and vans. This result reflects the shift in the ownership of vehicles from larger vehicles to smaller, fuel efficient, vehicles. The percentage change in overall usage shows a significant decrease in the use of pickup trucks and a marginal decrease in the use of all other motorized vehicle types. These results are fairly intuitive. Additionally, as expected, the results indicate that an increase in fuel cost results in a marginal increase in the use, and intensity of use, of non-motorized modes of transportation. Overall, however, the results reflect the rather small elasticity of vehicle holdings and use to fuel cost.

6.6 Summary

This chapter presented the empirical results of the analysis of vehicle holdings and usage decisions. The results provide important insights into the effect of household demographics, location attributes, built environment characteristics, household head characteristics and vehicle attributes on vehicle holdings and usage decisions. In addition, the chapter presents an application of the model in predicting the impact of transportation policy actions on vehicle holdings and usage decisions.

Chapter 7. Conclusions

The broad objective of this dissertation is to develop a comprehensive econometric model to examine several dimensions of the household vehicle holdings and usage decisions. Specifically, the intent of the research is to address the issue of households potentially holding a mix of different vehicle types, vintages and makes and models, jointly with the annual usage of each vehicle type/vintage.

This dissertation seeks to contribute to the vast literature in the area of automobile demand modeling by examining the impact of household demographics, location attributes, built environment characteristics, household head characteristics and vehicle attributes on vehicle holdings and usage decisions. In this context, an extensive survey of this literature was conducted to guide our efforts toward the development of a theory of vehicle type/vintage choice, make/model choice and usage decision-making. Next, a comprehensive framework of vehicle type/vintage/make/model choice and usage decision-making was developed that incorporates all the observed and unobserved factors that potentially influence the decision of the household, while also considering the processes that motivate the household to own and use multiple vehicle types, dynamics of vehicle ownership duration, influence of past vehicle ownership decisions and heterogeneity in the preferences of households. Subsequently, the proposed conceptual framework was translated into a general econometric model to examine a choice situation characterized by the simultaneous choice of multiple vehicle types/vintages by the household as well as the choice of a single make/model from a subset of alternatives for each vehicle type/vintage. Specifically, we used a nested structure with multiple discrete-continuous extreme value (MDCEV) model for the choice of vehicle type/vintage (discrete component) and usage (continuous component) in the upper level nest and a multinomial logit (MNL) model for the choice of vehicle make/model in the lower level nest. Finally, models were estimated using data from the 2000 Bay Area Travel Survey and the impact of a comprehensive set of variables on the vehicle holdings and usage decisions were examined. The empirical results provide important insights into the determinants of vehicle holdings and usage decisions of households. In addition, the model was applied to assess the potential impact of urban form and fuel cost related policies on household vehicle holdings and usage decisions.

This chapter first presents the contributions of this study (section 7.1). Important empirical results are then summarized (section 7.2). Finally, directions for further research are identified (section 7.3).

7.1 Contributions

This section discusses the contributions of this dissertation to the area of automobile demand modeling. Specifically, these contributions are broadly classified into two categories: (1) modeling methodology, and (2) model application.

7.1.1 Modeling Methodology

The dissertation presents a comprehensive modeling methodology for examining the vehicle holdings and usage decisions. First, the model examines several dimensions of vehicle holdings and use. In particular, we model number of vehicles owned as well as the following attributes for each of the vehicles owned: (1) vehicle body type, (2) vehicle age (i.e., vintage), (3) vehicle make and model, and (4) vehicle usage. Second, the model incorporates a comprehensive set of determinants of vehicle holdings and usage decisions, including household demographics, individual characteristics, household location attributes, vehicle attributes, fuel cost, and built environment characteristics. Third, the model accommodates for multiple discreteness (choice of multiple alternatives simultaneously) in the mix of the different types of vehicles owned by the household. Additionally, the model explicitly captures the diminishing marginal returns (*i.e.* satiation) from choice of a single vehicle type. These satiation effects lead to the preference of a household to own one or more vehicle types. Finally, the model can represent a choice situation characterized by the joint choice of (1) multiple alternatives from a set of mutually exclusive alternatives (*i.e.* alternatives are imperfect substitutes), and (2) a single alternative from a set of mutually exclusive alternatives (*i.e.* alternatives are perfect substitutes). Such a choice situation better characterizes the decision-making process of a multiple-vehicle household and cannot be handled by classical discrete and discrete-continuous models which assume that the alternatives are perfect substitutes of each other. Specifically, we use a multinomial logit structure to analyze the choice of a single make and model within each vehicle type/vintage chosen, and nest this MNL structure within an MDCEV formulation to analyze the simultaneous choice of multiple vehicle types/vintages and usage decisions. Further, we extend the joint MDCEV-MNL model to accommodate for heteroscedasticity and/or error correlation in both the multiple discrete-continuous component and the single discrete choice component of the joint model using a mixing distribution. The joint model also incorporates random coefficients in one or both components of the joint model. The resulting model is very flexible, and is able to accommodate general patterns of perfect and imperfect substitution among alternatives.

7.1.2 Model Application

The dissertation demonstrates the application of the joint MDCEV-MNL model. Specifically, the model estimated in this dissertation can predict the impact of different transportation policies such as increase in fuel cost, street block density or bike lane density, on vehicle holdings and usage. These predictions can be analyzed further to understand the broader implications of these transportation policies at a community and regional level and its implications on greenhouse gas emissions, traffic congestion and energy consumption. In particular, such predictions can inform the design of proactive land-use, economic, and transportation policies to influence household vehicle holdings and usage in a way that reduces the negative impacts of automobile dependency such as traffic congestion, fuel consumption and air pollution.

7.2 Summary of Important Empirical Results

The empirical model in this dissertation was estimated using data from 2000 San Francisco Bay Survey. In addition, supplementary data on vehicle make/model attributes, residential location variables and built environment attributes is also used. The empirical results provide important insights into the determinants of vehicle holdings and usage decisions of households. Some important findings from the impact of household demographics, location attributes, built environment characteristics, household head characteristics and vehicle attributes on vehicle holdings and usage decisions, and satiation effects are presented below.

The demographic variable effects indicate that high income households have a lower baseline preference for older vehicles relative to low/middle income households, as expected. A similar result is observed for households with more number of employed members. It is also interesting to note that both high income households and households with more number of employed members are less likely to use non-motorized forms of transportation compared to other households. Further, the results show that households with very small children (less than or equal to 4 years of age) are more likely to use compact sedans and mid-size sedans than other households. Similar results are observed for households with senior adults.

The effects of household location attributes and built environment characteristics of the household residential neighborhood indicate that households located in urban areas or in dense residential or commercial/industrial neighborhoods are less likely to own/use large vehicle types such as pickup trucks and vans compared to other households. Also, households located in residential neighborhood with high bike lane density are more likely to use non-motorized modes of transportation, while those located in neighborhoods with high street block density are more likely to prefer compact vehicles.

The effects of household head characteristics indicate that households with older household heads are generally more likely to own vehicles of an older vintage compared to younger households. Further, the results point to a higher baseline preference for older and larger vehicles if the male is the oldest member (or only adult) in the household relative to households with the female being the oldest member (or only adult).

The effects of vehicle attributes show that households prefer vehicle makes/models which are less expensive to purchase and operate, which have high luggage volume and seating capacity, high engine performance and low greenhouse gas emissions, amongst other things.

Finally, the satiation effects indicate clear satiation in vehicle holding and usage decisions. The results show that middle and high income households are more likely to get satiated with the increasing use of any vehicle type/vintage compared to low income households, as expected. Further, low income households are least likely to get satiated with the increasing use of old subcompact sedans, new and old compact sedans, and old midsize sedans.

7.3 Directions for Further Research

There are several areas for further research in the area of vehicle holdings and usage models. Some of the important directions for further research are presented below.

The additional use of dimensions that capture the dynamic effects in the vehicle holdings and usage decisions such as duration of vehicle ownership and vehicle transaction type, can better predict the change in the vehicle fleet mix between two given points in time. Specially, the use of these dimensions will closely tie the models to the actual household decision-making process which involves a series of transaction decisions to acquire, replace, and dispose of household vehicles. Further, these dynamic models can accommodate for (1) the duration dynamics which explains the year to year variation in vehicle ownership behavior and (2) the state dependence which explains the influence of past vehicle ownership decisions on the current vehicle ownership. This can lead to better and unbiased estimations of the effect of time on the changes in the vehicle ownership of households. These considerations require detailed year to year data on the vehicle transaction and necessitate the development of appropriate modeling methodologies.

This dissertation has focused on the impact of household demographics, location attributes, built environment characteristics, household head characteristics and vehicle attributes on vehicle holdings and usage decisions. It would be interesting to examine the impact of attitudinal factors such as perception of mobility, liking for travel, personality, lifestyle, attitude towards driving, and perception of safety, on vehicle holdings and use. These potential determinants of vehicle holdings and use can further enrich the empirical specification for the model used in this dissertation.

Another important area of further research is to enhance the model used in this dissertation. The model used here does not capture the possible endogeneity or correlation of observed vehicle attributes such as purchase price of the vehicle with unobserved attributes. It would be useful to examine the possible endogeneity of explanatory variables and correct it to ensure that there is no bias in the parameter estimates.

Table 1. Distribution of Vehicles

No. of vehicles owned by household	Total number of households	Percentage of households
1	4459	55%
2	2918	36%
3	644	8%
4 and more	86	1%

Table 2. Descriptive Statistics of Vehicle Type/Vintage Holdings

Vehicle type/vintage	Total number (%) of households owning	Annual Mileage	No. of households who own (%)	
			Only Vehicle type/vintage	Vehicle type/vintage and other Vehicle type/vintages
New Coupe	389 (5%)	7763	132 (34%)	257 (66%)
Old Coupe	1024 (13%)	7766	374 (37%)	650 (63%)
New Subcompact Sedan	292 (4%)	7838	127 (43%)	165 (57%)
Old Subcompact Sedan	513 (6%)	9570	238 (46%)	275 (54%)
New Compact Sedan	767 (9%)	8321	342 (45%)	425 (55%)
Old Compact Sedan	1175 (14%)	9614	495 (42%)	680 (58%)
New Midsize Sedan	987 (12%)	7688	361 (37%)	626 (63%)
Old Midsize Sedan	1543 (19%)	9342	636 (41%)	907 (59%)
New Large Sedan	250 (3%)	7418	71 (28%)	179 (72%)
Old Large Sedan	377 (5%)	8339	151 (40%)	226 (60%)
New Station Wagon	242 (3%)	7869	80 (33%)	162 (67%)
Old Station Wagon	728 (9%)	8248	254 (35%)	474 (65%)
New SUV	707 (9%)	8920	245 (35%)	462 (65%)
Old SUV	711 (9%)	9813	213 (30%)	498 (70%)
New Pickup Truck	578 (7%)	8887	153 (26%)	425 (74%)
Old Pickup Truck	1198 (15%)	8679	301 (25%)	897 (75%)
New Minivan	459 (6%)	9156	115 (25%)	344 (75%)
Old Minivan	480 (6%)	9890	130 (27%)	350 (73%)
New Van	39 (1%)	10640	8 (21%)	31 (79%)
Old Van	122 (2%)	8203	33 (27%)	89 (73%)
Non-Motorized form of transportation	201 (3%)	2695	-	201 (100%)

Table 3. Descriptive Statistics of Two-Vehicle Households

Vehicle type and vintage (Vehicle 1)	**Total number (%) of households owning Vehicle 1 and any other**	**Total number of households (%) that own Vehicle 1 and other vehicle types (most popular combinations only)**	
		Vehicle 1 and Vehicle 2	
New Coupe	182 (6%)	Old Pickup Truck	23 (13%)
Old Coupe	431 (15%)	Old Midsize Sedan	59 (14%)
New Subcompact Sedan	127 (4%)	New Midsize Sedan	18 (14%)
Old Subcompact Sedan	205 (7%)	Old Midsize Sedan	20 (10%)
New Compact Sedan	327 (11%)	Old Compact Sedan	48 (15%)
Old Compact Sedan	519 (18%)	Old Pickup Truck	69 (13%)
New Midsize Sedan	476 (16%)	Old Midsize Sedan	62 (13%)
Old Midsize Sedan	663 (23%)	Old Pickup Truck	84 (13%)
New Large Sedan	124 (4%)	Old Midsize Sedan	25 (20%)
Old Large Sedan	165 (6%)	Old Pickup Truck	30 (18%)
New Station Wagon	123 (4%)	Old Station Wagon	15 (12%)
Old Station Wagon	321 (11%)	Old Compact Sedan	41 (13%)
New SUV	341 (12%)	New Midsize Sedan	47 (14%)
Old SUV	341 (12%)	Old Midsize Sedan	46 (13%)
New Pickup Truck	320 (11%)	Old Midsize Sedan	43 (13%)
Old Pickup Truck	595 (20%)	Old Midsize Sedan	84 (14%)
New Minivan	271 (9%)	Old Midsize Sedan	56 (21%)
Old Minivan	234 (8%)	Old Midsize Sedan	32 (14%)
New Van	20 (1%)	Old Pickup Truck	4 (20%)
Old Van	51 (2%)	Old Pickup Truck	10 (20%)

Table 4. MDCEV Model Results – Parameters (and t-statistic)

	Old Coupe	New Sub Compact Sedan	Old Sub Compact Sedan	New Compact Sedan	Old Compact Sedan	New Mid-size Sedan	Old Mid-size Sedan	New Large Sedan	Old Large Sedan	New Station Wagon
Household Demographics										
Annual household income dummy variables										
Medium annual income (35K-90K)	-	-	-	-	-	-	-	-	-	-
High annual income (>90K)	-0.378 (-6.03)	-	-0.378 (-6.03)	-0.438 (-5.60)	-0.378 (-6.03)	-	-0.378 (-6.03)	-	-0.378 (-6.03)	-
Presence of children in the household										
Presence of children < = 4 yrs	-	-	0.334 (4.68)	0.392 (5.04)	0.334 (4.68)	0.392 (5.04)	0.334 (4.68)	-	-	-
Presence of children b/w 5 and 15 yrs	-	-	-	-	0.244 (4.27)	-	0.244 (4.27)	-	-	-
Presence of children b/w 16 and 17 yrs	-	-	-	-	-	-	-	-	-	-
Presence of senior adults (> 65 years) in the household	-	-	-	0.423 (6.09)	0.574 (9.18)	0.423 (6.09)	0.574 (9.18)	1.172 (11.78)	1.172 (11.78)	-
Household size	-	-	-	-	-	0.074 (2.84)	0.139 (7.33)	0.494 (13.29)	0.139 (7.33)	0.074 (2.84)
Number of employed individuals in the household	-	0.161 (4.43)	-	0.161 (4.43)	-	-	-	-0.419 (-8.89)	-0.193 (-4.36)	-

Table 4 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Station Wagon	New SUV	Old SUV	New Pickup Truck	Old Pickup Truck	New Minivan	Old Minivan	New Van	Old Van	Non-Mot. Transp.
Household Demographics										
Annual household income dummy variables										
Medium annual income (35K-90K)	0.159 (1.96)	0.662 (2.63)	-	-	0.223 (3.79)	-	0.223 (3.79)	-	-0.633 (-2.24)	-
High annual income (>90K)	-0.378 (-6.03)	0.663 (2.56)	-0.378 (-6.03)	-0.438 (-5.60)	-0.378 (-6.03)	-	-0.378 (-6.03)	-	-1.452 (-4.13)	-0.378 (-6.03)
Presence of children in the household										
Presence of children < = 4 yrs	-	0.392 (5.04)	0.334 (4.68)	-	-	0.392 (5.04)	-	-	-0.924 (-2.24)	-
Presence of children b/w 5 and 15 yrs	-	-	-	-	-	0.809 (6.93)	0.656 (5.17)	-	-	-
Presence of children b/w 16 and 17 yrs	-	-	-	-	-	-	-	-	-0.618 (-1.53)	-
Presence of senior adults (> 65 years) in the household	0.423 (6.09)	-	-	-	-	-	-	-	0.574 (9.18)	0.574 (9.18)
Household size	0.139 (7.33)	0.074 (2.84)	0.139 (7.33)	-	0.139 (7.33)	0.494 (13.29)	0.563 (12.87)	0.494 (13.29)	0.563 (12.87)	0.494 (13.29)
Number of employed individuals in the household	-	-	-	0.161 (4.43)	-	-0.419 (-8.89)	-0.193 (-4.36)	-	-	-0.419 (-8.89)

Table 4 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Coupe	New Sub Compact Sedan	Old Sub Compact Sedan	New Compact Sedan	Old Compact Sedan	New Mid-size Sedan	Old Mid-size Sedan	New Large Sedan	Old Large Sedan	New Station Wagon
Household Location Attributes										
Zonal dummy variables (urban is base)										
Suburban	-	-	-0.257 (-4.68)	-	-0.257 (-4.68)	-	-	0.281 (2.45)	-	-
Rural	-	-	-	-	-	-	-	-	-	-0.678 (-1.72)
Employment Density	-	-	-	-	-	-	-	-	-	-
Built Environment Characteristics of the Residential Neighborhood										
Land Use Structure Variables										
Residential Acres within 1 mile radius	-	-	-	-	-	-	-	-	-	-
Commercial / Industrial Acres within 1 mile radius	-	-	-	-	-	-0.268 (-2.73)	-0.268 (-2.73)	-	-	-0.268 (-2.73)
Number of Households in Multi-family Dwelling Units within 1 mile radius (in 10,000's)	-	-	-	-	-	-	-	-0.464 (-4.43)	-0.464 (-4.43)	-
Local Transportation Network Measures										
Bike Lane Density (Total miles of bikeway within 0.25 mile radius)	-	-	-	-	-	-	-	-	-	-
Street Block Density (Number of Street Blocks within 1 mile radius)	-	0.678 (3.95)	0.998 (3.99)	0.678 (3.95)	0.998 (3.99)	-	-	-	-	0.678 (3.95)

Table 4 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Station Wagon	New SUV	Old SUV	New Pickup Truck	Old Pickup Truck	New Minivan	Old Minivan	New Van	Old Van	Non-Mot. Transp.
Household Location Attributes										
Zonal dummy variables (urban is base)										
Suburban	-0.257 (-4.68)	-	-	0.281 (2.45)	0.166 (2.01)	-	-	-	-	0.166 (2.01)
Rural	-	-	-	0.349 (1.77)	0.232 (1.59)	-	-	-	-	-
Employment Density	-	-	-	-0.003 (-2.39)	-	-	-	-	-	-
Built Environment Characteristics of the Residential Neighborhood										
Land Use Structure Variables										
Residential Acres within 1 mile radius	-	-	-	-0.408 (-6.79)	-0.408 (-6.79)	-	-	-0.364 (-2.09)	-0.364 (-2.09)	-
Commercial / Industrial Acres within 1 mile radius	-0.268 (-2.73)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-0.332 (-3.29)	-	-	-
Number of Households in Multi-family Dwelling Units within 1 mile radius (in 10,000's)	-	-	-	-	-	-	-	-	-	-
Local Transportation Network Measures										
Bike Lane Density (Total miles of bikeway within 0.25 mile radius)	-	-	-	-	-	-	-	-	-	1.559 (3.27)
Street Block Density (Number of Street Blocks within 1 mile radius)	0.998 (3.99)	-	-	-	-	-	-	-	-	-

Table 4 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Coupe	New Sub Compact Sedan	Old Sub Compact Sedan	New Compact Sedan	Old Compact Sedan	New Mid-size Sedan	Old Mid-size Sedan	New Large Sedan	Old Large Sedan	New Station Wagon
Household Head Characteristics										
Age (age < = 30 yrs is base)										
Age between 31 and 45 yrs	-	-0.586 (-5.99)	-	-0.586 (-5.99)	-	-	0.211 (3.32)	-	-	-0.586 (-5.99)
Age greater than 45 yrs of age	0.245 (4.48)	-1.031 (-7.22)	-	-0.602 (-5.86)	-	-	0.644 (8.70)	0.909 (6.19)	0.644 (8.70)	-0.602 (-5.86)
Male	0.288 (4.88)	-0.267 (-3.76)	-	-0.271 (-3.81)	-	-	-	0.445 (6.08)	-	-
Ethnicity (Caucasian is base)										
African-American	-	-	-	-	-	-	-	-	0.807 (3.05)	-
Hispanic	-	-	-	-	-	-	-	-	0.545 (2.21)	-
Asian	-	0.641 (7.69)	0.462 (5.49)	0.641 (7.69)	0.462 (5.49)	0.641 (7.69)	0.462 (5.49)	-	-	-0.989 (-4.33)
Other	-	0.414 (2.39)	0.354 (2.83)	-	-	-	-	-	0.354 (2.83)	-
Baseline Preference Constants	0.368 (2.88)	0.508 (2.82)	0.528 (3.90)	0.945 (6.28)	0.747 (5.57)	0.800 (6.62)	0.356 (2.51)	-1.958 (-8.04)	-0.435 (-2.55)	0.445 (2.22)

Table 4 (continued). MDCEV Model Results – Parameters (and t-statistic)

	Old Station Wagon	New SUV	Old SUV	New Pickup Truck	Old Pickup Truck	New Minivan	Old Minivan	New Van	Old Van	Non-Mot. Transp.
Household Head Characteristics										
Age (age < = 30 yrs is base)										
Age between 31 and 45 yrs	-	-	-	-	0.211 (3.32)	0.628 (3.73)	0.211 (1.79)	-	0.211 (1.79)	0.211 (3.32)
Age greater than 45 yrs of age	0.245 (4.48)	-	-	-	0.245 (4.48)	0.909 (6.19)	0.644 (8.70)	-	0.644 (8.70)	0.644 (8.70)
Male	-	-	0.288 (4.88)	0.445 (6.08)	0.489 (7.00)	0.445 (6.08)	-	-	0.489 (7.00)	-
Ethnicity (Caucasian is base)										
African-American	-	-	-0.619 (-1.80)	-0.679 (-1.77)	-	-	-	-	-	-
Hispanic	-	-	-	-	-	-	-	-	-1.777 (-1.63)	-
Asian	-	-	-	-0.989 (-4.33)	-0.597 (-3.81)	0.641 (7.69)	-	-	-0.597 (-3.81)	-
Other	0.354 (2.83)	-	-	-	-	0.414 (2.39)	-	1.082 (1.99)	-	-
Baseline Preference Constants	0.043 (0.27)	0.104 (0.35)	1.539 (4.94)	0.536 (2.83)	0.763 (4.23)	-0.962 (-2.89)	-0.627 (-1.96)	-2.284 (-5.79)	-1.225 (-2.91)	1.431 (1.96)

Table 5. Multinomial Logit Model Results for Vehicle Make/Model Choice

Variable	Parameter	t-stat
Cost Variables		
Purchase Price (in $)/Income (in $/yr) [x 10]		
Mean Effect	-0.173	-5.71
Standard Deviation	0.064	4.44
Fuel Cost (in $/yr) /Income (in $/yr) [x 10]	-0.003	-1.61
Internal Vehicle Dimensions		
Seat Capacity * Household Size less than equal to 2 dummy variable	-0.075	-5.11
Luggage Volume (in 10s of cubic feet)	0.023	3.54
Standard Payload Capacity (for Pickup Trucks only) (in 1000 lbs)	0.196	5.13
Vehicle Performance Indicators		
Horsepower (in HP) /Vehicle Weight (in lbs) [in 10s]	1.102	4.89
Engine Size (in liters)	-0.045	-2.42
Type of Drive Wheels and Vehicle Makes		
Dummy variable for All-Wheel-Drive (base: rear-wheel-drive)	-0.214	-3.81
Dummy Variable for Vehicle Make - Chevy	-0.149	-1.25
Dummy Variable for Vehicle Make - Ford	0.716	5.37
Dummy Variable for Vehicle Make - Honda	1.444	5.37
Dummy Variable for Vehicle Make - Toyota	0.752	5.29
Dummy Variable for Vehicle Make - Cadillac	0.880	4.36
Dummy Variable for Vehicle Make - Volkswagen	0.374	2.55
Dummy Variable for Vehicle Make - Dodge	0.699	4.96
Fuel Emissions and Type		
Amount of Greenhouse Gas Emissions (in 10s of tons/yr)	-0.429	-2.71
Dummy variable for Premium Fuel (base: regular fuel)	-0.552	-5.01

Table 6. Satiation Effects

Vehicle Type/Vintage	Parameter	t-statistic
New Coupe		
Low Income Households	0.9036	4.05
Medium Income Households	0.8196	3.45
High Income Households	0.7344	3.87
Old Coupe		
Low Income Households	0.8929	6.59
Medium Income Households	0.7794	5.68
High Income Households	0.7280	5.94
New Subcompact Sedan		
Low and Medium Income Households	0.9066	4.29
High Income Households	0.7413	3.98
Old Subcompact Sedan		
Low Income Households	0.9574	4.15
Medium Income Households	0.9050	3.78
High Income Households	0.8783	3.84
New Compact Sedan		
Low Income Households	0.9242	4.41
Medium Income Households	0.8553	3.52
High Income Households	0.7826	3.87
Old Compact Sedan		
Low Income Households	0.9361	5.95
Medium Income Households	0.8612	4.98
High Income Households	0.8246	5.09
New Midsize Sedan		
Low Income Households	0.8985	4.75
Medium Income Households	0.8110	3.81
High Income Households	0.7231	4.30
Old Midsize Sedan		
Low Income Households	0.9293	6.30
Medium Income Households	0.8478	5.21
High Income Households	0.8084	5.34
New Large Sedan		
Constant	0.7723	5.83

Table 6 (continued). Satiation Effects

Vehicle Type/Vintage	Parameter	t-statistic
Old Large Sedan		
Constant	0.8485	6.11
New Station Wagon		
Low and Medium Income Households	0.8893	4.40
High Income Households	0.7034	4.21
Old Station Wagon		
Low Income Households	0.9051	6.03
Medium Income Households	0.8018	5.28
High Income Households	0.7540	5.50
New SUV		
Constant	0.8167	9.25
Old SUV		
Constant	0.8338	8.48
New Pickup Truck		
Low Income Households	0.8741	4.70
Medium Income Households	0.7710	3.92
High Income Households	0.6720	4.53
Old Pickup Truck		
Low Income Households	0.8481	7.63
Medium Income Households	0.7029	6.63
High Income Households	0.6419	7.07
New Minivan		
Constant	0.7698	8.02
Old Minivan		
Constant	0.8100	7.32
New Van		
Constant	0.8009	2.18
Old Van		
Low and Medium Income Households	0.8280	3.50
High Income Households	0.6072	4.35
Non-motorized form of transportation		
Constant	0.2211	5.56

Table 7. Impact of Change in Built Environment Variables and Fuel Cost

Vehicle Type	Impact of a 25% increase in bike lane density		Impact of a 25% increase in street block density		Impact of a 25% increase in fuel cost	
	% change in holdings of vehicle type	% change in overall use of vehicle type	% change in holdings of vehicle type	% change in overall use of vehicle type	% change in holdings of vehicle type	% change in overall use of vehicle type
Compact Car	-	-2.2%	8.5%	3.4%	1.3%	-0.9%
Midsize and Large Sedan	-2.2%	-2.1%	-	-0.8%	-	-0.6%
SUV	-0.6%	-0.4%	-	-	-	-
Pickup Truck	-1.4%	-0.4%	-2.1%	-1.7%	-5.7%	-2.3%
Minivan and Van	-	-0.7%	-	-0.6%	-2.6%	-
Non-motorized modes of transportation	7.4%	13.9%	-4.0%	-3.3%	1.5%	0.8%

Vehicle Type/ Vintage		
	New Coupe	23 makes/models
	Old Coupe	33 makes/models
	New Subcompact Sedan	7 makes/models
	Old Subcompact Sedan	10 makes/models
	New Compact Sedan	19 makes/models
	Old Compact Sedan	25 makes/models
	New Mid-size Sedan	21 makes/models
	Old Mid-size Sedan	24 makes/models
	New Large Sedan	12 makes/models
	Old Large Sedan	16 makes/models
	New Station Wagon	12 makes/models
	Old Station Wagon	23 makes/models
	New SUV	23 makes/models
	Old SUV	15 makes/models
	New Pickup Truck	13 makes/models
	Old Pickup Truck	12 makes/models
	New Minivan	15 makes/models
	Old Minivan	13 makes/models
	New Van	5 makes/models
	Old Van	6 makes/models
	Non-motorized vehicles	

Figure 2. Classification of Vehicle Type/Vintage

References

Berkovec, J. (1985). Forecasting automobile demand using disaggregate choice models, *Transportation Research Part B*, Vol. 19, No. 4, pp. 315–329.

Berkovec, J. and Rust, J. (1985). A nested logit model of automobile holdings for one vehicle households, *Transportation Research Part B*, Vol. 19, No. 4, pp. 275–285.

Berry, S. (1994). Estimating Discrete Choice Models with Product Differentiation, *RAND Journal of Economics,* Vol. 25, pp. 242-262.

Berry, S., Levinsohn, J. and Pakes, A. (1995). Automobile prices in market equilibrium, *Econometrica*, Vol. 63, No. 4, pp. 841–890.

Berry, S.T., Levinsohn, J. and Pakes, A. (1999). Voluntary Export Restraints on Automobiles: Evaluating a Strategic Trade Policy, *American Economic Review*, Vol. 89, pp. 400-430.

Berry, S.T., Levinsohn, J. and Pakes, A. (2004), Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Vehicle Market, *Journal of Political Economy*, Vol. 112, pp. 68-105.

Burns, L.D. and Golob, T.F. (1976). The role of accessibility in basic transportation choice behavior, *Transportation*, No. 5, pp. 175-198.

Bhat, C.R. (1995). A Heteroscedastic Extreme Value Model of Intercity Mode Choice, *Transportation Research Part B*, Vol. 29, No. 6, pp. 471-483.

Bhat, C.R. (1998). Accommodating Flexible Substitution Patterns in Multidimensional Choice Modeling: Formulation and Application to Travel Mode and Departure Time Choice, *Transportation Research Part B*, Vol. 32, No. 7, pp. 455-466

Bhat, C. and Pulugurta, V. (1998). A Comparison of Two Alternative Behavioural Choice Mechanisms for Household Auto Ownership Decisions, *Transportation Research Part B*, Vol 32, No. 1, pp. 61-75.

Bhat, C.R., Handy, S., Kockelman, K., Mahmassani, H.S., Chen, Q. and Weston, L. (2000). Development of an Urban Accessibility Index: Literature Review, Report 4938-1, prepared for the Texas Department of Transportation.

Bhat, C.R. (2000a). Duration Modeling, *Handbook of Transport Modelling*, pp. 91-111, Edited by D. A. Hensher and K.J. Button, Elsevier Science.

Bhat, C.R. (2000b). Incorporating Observed and Unobserved Heterogeneity in Urban Work Mode Choice Modeling, *Transportation Science*, Vol. 34, No. 2, pp. 228-238.

Bhat, C.R. and Castelar, S. (2002). A Unified Mixed Logit Framework for Modeling Revealed and Stated Preferences: Formulation and Application to Congestion Pricing Analysis in the San Francisco Bay Area, *Transportation Research Part B*, Vol. 36, No. 7, pp. 593-616.

Bhat, C.R. (2003a). Random Utility-Based Discrete Choice Models for Travel Demand Analysis, *Transportation Systems Planning: Methods and Applications*, Chapter 10, pp. 1-30, Edited by K. Goulias, CRC Press.

Bhat, C.R. (2003b). Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences, *Transportation Research Part B*, Vol. 37, No. 9, pp. 837-855.

Bhat, C.R. (2005). A Multiple Discrete-Continuous Extreme Value Model: Formulation and Application to Discretionary Time-Use Decisions, *Transportation Research Part B*, Vol. 39, No. 8, pp. 679-707.

Bhat, C.R., and Guo, J.Y. (2005). A Comprehensive Analysis of Built Environment Characteristics on Household Residential Choice and Auto Ownership Levels, Technical paper, Department of Civil Engineering, The University of Texas at Austin.

Bhat, C.R. and Sen, S. (2006). Household Vehicle Type Holdings and Usage: An Application of the Multiple Discrete-Continuous Extreme Value (MDCEV) Model, *Transportation Research Part B*, Vol. 40, No. 1, pp. 35-53.

Bhat, C.R., Srinivasan, S. and Sen, S. (2005a). A Joint Model for the Perfect and Imperfect Substitute Goods Case: Application to Activity Time-Use Decisions, forthcoming, *Transportation Research Part B*.

Bhat, C.R., Srinivasan, S. and Axhausen, K.W. (2005b). An Analysis of Multiple Interepisode Durations Using a Unifying Multivariate Hazard Model, *Transportation Research Part B*, Vol. 39, No. 9, pp. 797-823.

Birkeland, M.E. and Jørgensen, J.J. (2001). Energy Efficiency of Passenger Cars, *Paper for European Transport Conference*, PTRC, Cambridge.

Ben-Akiva, M. E. (1974). Structure of passenger travel demand models, *Transportation Research Record*, 526.

Bjorner, T.B. and Petersen, S.L. (2004). Dynamic Models of Car Ownership at the Household Level, Working Paper, AKF, Institute of Local Government Studies, Denmark.

Boyd, J. and Mellman, R. (1980). The Effect of Fuel Economy Standards on the U.S. Automotive Market: An Hedonic Demand Analysis, *Transportation Research Part A*, Vol. 14, Nos. 5-6, pp. 367-378.

Brownstone, D., Bunch, D., Golob, T. and Ren, W. (1996). Transactions choice model for forecasting demand for alternative-fuel vehicles, In: McMullen, S. (Ed.), Research in *Transportation Economics*, Vol. 4, JAI Press, pp. 87-129.

Brownstone, D. and Train, K. (1999). Forecasting new product penetration with flexible substitution patterns, *Journal of Econometrics*, Vol. 89, Nos. 1-2, pp. 109-129.

Brownstone, D., Bunch, D. and Train, K. (2000). Joint Mixed Logit Models of Stated and Revealed Preferences for Alternative-Fuel Vehicles, *Transportation Research Part B*, Vol 34, No. 5, pp. 315-338.

Bunch, D.S., Bradley, M., Golob, T.F., Kitamura, R. and Occhiuzzo G.P. (1993). Demand for Clean-Fuel Vehicles in California: A Discrete-Choice Stated Preference Survey, *Transportation Research Part A*, Vol. 27, No. 3, pp. 237-253.

Bunch, D. S., Brownstone, D. and Golob, T. F. (1996). A dynamic forecasting system for vehicle markets with clean-fuel vehicles, *World Transport Research*, Vol. 1, pp. 189–203.

Bunch, D.S. (2000). Automobile demand and type choice, *Handbook of transport Modeling*, Capitulo.

Cao, X.Y., Mokhtarian, P.L. and Handy, S.L. (2006). Neighborhood design and vehicle type choice: Evidence from Northern California, *Paper presented at the 85th TRB Annual Meeting*.

Cardell, N. and Dunbar, F. (1980). Measuring the Societal Impacts of Automobile Downsizing, *Transportation Research Part A*, Vol. 14, Nos. 5-6, pp. 423-434.

Carlson, D., Wormser, L. and Ulberg, C. (1995). *At Road's End; Transportation and Land Use Choices for Communities*, Island Press, Washington DC, p. 15.

CES (2004). Consumer Expenditures in 2002, U.S. Department of Labor, Bureau of Labor Statistics, Report 974.

Chamberlain, G. (1980). Analysis of Covariance with Qualitative Data, *Review of Economic Studies*, Vol. 47, pp. 225-238.

Chintagunta, P. K., and Prasad, A. R. (1998). An Empirical Investigation of the 'Dynamic McFadden' Model of Purchase Timing and Brand Choice: Implications for Market Structure, *Journal of Business and Economic Statistics,* No. 16, pp. 2-12.

Choo, S. and Mokhtarian, P.L. (2004). What type of vehicle do people drive? The role of attitude and lifestyle in influencing vehicle type choice, *Transportation Research Part A*, Vol. 38, No. 3, pp. 201–222.

Chow, G. (1957). Demand for Automobiles in the United States, North-Holland, Amsterdam.

Consumer Guide (2005). Consumer Guide Automotive, website: http://auto.consumerguide.com/

CS (1997). Vehicle availability modeling, Vol. 1, Final report prepared for Federal Highway Administration, Cambridge Systematics, Inc.

Dargay, J. and Gately, D. (1999). Income's effect on car and vehicle ownership, worldwide: 1960–2015, *Transportation Research Part A*, Vol. 33, No. 2, pp. 101–138.

Dargay J.M. and Vythoulkas, P.C. (1999). Estimation of a Dynamic Car Model: A Pseudo-Panel Approach, *Journal of Transport Economics and Policy*, Vol. 33, Part 3, pp. 287-302.

Diggle, P.J., Liang, K-Y. and Zeger, S.L. (1994). *Analysis of Longitudinal Data*, Clarendon Press, Oxford.

Dube, J.P. (2004). Multiple discreteness and product differentiation: Demand for carbonated soft drinks, *Marketing Science*, Vol. 23, No. 1, pp. 66-81.

Dubin, J. and McFadden, D. (1984). An Econometric Analysis of Residential Electric Appliance Holding and Consumption, *Econometrica*, Vol. 52, No. 2, pp. 53-76.

Engwicht, D. (1993). Reclaiming our Cities and Towns, New Society Publishers, Philadelphia, p. 45.

EPA Report (1999). Indicators of the Environmental Impacts of Transportation, United States Environmental Protection Agency, EPA 230-R-99-001

EPA (2005). Fuel Economy Guide, Environmental Protection Agency and U.S. Department of Energy, website: http://www.fueleconomy.gov/feg/findacar.htm

EPA (2006). United States Environmental Protection Agency, website: http://epa.gov/

Feng, Y., Fullerton, D. and Gan, L. (2004). Vehicle Choices, Miles Driven, and Pollution Policies, Department of Economics, The University of Texas at Austin.

Gallez, C. (1994). Identifying the long term dynamics of car ownership, a demographic approach, *Transport Reviews*, Vol. 14, No. 1, pp 83-102.

Gilbert, C.S. (1992) A duration model of automobile ownership, *Transportation Research Part B*, Vol. 26, No. 2, pp. 97–114.

Goldberg, P.K. (1998). The Effects of the Corporate Average Fuel Efficiency Standards in the US, *Journal of Industrial Economics*, Vol. 46, No. 1, pp. 1-33.

Golob T. E, and Burns L. D. (1978). Effects of transportation service on automobile ownership in an urban area, *Transportation Resesearch Record*, 673, pp. 137-145.

Golob, T. F. and Wissen, L.V. (1989). A joint household travel distance generation and car ownership model, *Transportation Research Part B*, Vol. 23, No. 6, pp. 471–491.

Golob, T.F. (1990). The Dynamics of Travel Time Expenditures and Car Ownership Decisions, *Transportation Research Part A*, Vol. 24, No. 6, pp. 443-463.

Golob, T.F., S. Kim and W. Ren. (1996). How Households Use Different Types of Vehicles: A Structural Driver Allocation and Usage Model, *Transportation Research Part A*, Vol. 30, No. 2, pp. 103-118.

Golob, T.F., Bunch D.S. and Brownstone, D. (1997). A Vehicle Use Forecasting Model Based on Revealed and Stated Vehicle Type Choice and Utilization Data, *Journal of Transport Economics and Policy*, Vol. 31, No. 1, pp. 69-92.

Golob, T.F. (2003). Structural equation modeling for travel behavior research, *Transportation Research Part B*, Vol.37, pp. 1–25.

Hanly, M. and Dargay, J.M. (2000) Car ownership in Great Britain: Panel data analysis,*Transportation Research Record*, 1718, pp. 83-89, Washington.

Hansen, M., and Huang, Y. (1997). Road supply and traffic in California urban areas. *Transportation Research Part A*, Vol. 31, No. 3, pp. 205-218.

Harrington, W. and McConnell, V. (2003). *Motor Vehicles and the Environment, Resources for the Future*, Washington, D.C.

Hendel, I. (1999). Estimating multiple-discrete choice models: An application to computerization returns, *Review of Economic Studies*, 66, pp. 423-446.

Hensher, D.A. and Greene W.G. (2001). Choosing between conventional, electric and LPG/CNG vehicles in single-vehicle households, In: Hensher DA (ed) *Travel Behaviour Research: The Leading Edge*, pp. 725–750, Oxford: Pergamon.

Hensher, D. A. and Mannering, F. (1994). Hazard-based duration models and their application to transport analysis, *Transport Reviews,* Vol. 14, No. 1, pp. 63-82.

Hensher, D.A. and Plastrier, V.L. (1985). Towards a Dynamic Discrete-Choice Model of Household Automobile Fleet Size and Composition, *Transportation Research Part B*, Vol. 19, No. 6, pp. 481-495.

Hensher, D.A. (1985). An Econometric Model of Vehicle Use in the Household Sector, *Transportation Research Part B*, Vol. 19, No. 4, pp. 303-314.

Hensher, D.A, Barnard, P.O., Smith, N.C. and Milthorpe, F.W. (1992). *Dimensions of automobile demand; a longitudinal study of automobile ownership and use*, North-Holland, Amsterdam.

Hocherman, I., Prashker, J.N. and Ben-Akiva, M. (1983). Estimation and use of dynamic transaction models of automobile ownership. *Transportation Research Record*, 944, pp. 134-141.

Hsiao, C. (1986). *Analysis of Panel Data*, Cambridge University Press, Cambridge.

Ingram, G. K. and Liu, Z. (1997). Motorization and the Provision of Roads in Countries and Cities, Policy Research Working Paper 1842 (Washington, DC: World Bank).

Jansson, J.O. (1989). Car demand modelling and forecasting. a new approach. *Journal of Transport Economics and Policy*, Vol. 13, No. 2, pp. 125-140.

Jeff, K., Laube, F. , Newman, P. and Barter, P. (1997). *Indicators of Transport Efficiency in 37 Global Cities, A report to The World Bank*. pp. 44

Jong G.C. (1990). An indirect utility model of car ownership and private car use. *European Economic Review*, 34, pp. 971-985.

Jong, G.C. and Kitamura, R. (1992). A review of household dynamic vehicle ownership models: holdings models versus transactions models, *Paper presented at the PTRC 20th Summer Annual Meeting*, Seminar E, London, UK.

Jong, G.C. (1996). A disaggregate model system of vehicle holding duration, type choice and use. *Transportation Research Part B*, Vol. 30, No. 4, pp. 263-276.

Jong, G.C., Vellay, C. and Fox, J. (2001). Vehicle scrappage: literature and a new stated preference survey, *Paper presented at the European Transport Conference*, PTRC, Cambridge, UK.

Jong, G.C., Fox, J., Daly, A., Pieters, M. and Smit, R. (2004). Comparison of Car Ownership Models, *Transport Reviews*, Vol. 24, No. 4, pp. 379–408

Kain, J.F. (1962). The Journey-to-work as a determinant of residential location, *Papers and Proceedings of the Regional Science Association*, Vol 9, pp. 137-160.

Kain, J.F. and Fauth, G.R. (1977). The Impact of Urban Development on Auto Ownership and Transit Use, Discussion Paper D77-18, Department of City and Regional Planning, Harvard University.

Kim, J., Allenby, G.M., and Rossi, P.E. (2002). Modeling consumer demand for variety, *Marketing Science*, 21, pp. 229-250.

Kitamura, R. (1989). The Asymmetry of the Change in Household Car Ownership and Utilization: A Panel Analysis. In *Travel Behaviour Research*. (The International Association for Travel Behaviour, ed.) Avebury Press, Aldershot, U.K., pp. 186–197.

Kitamura, R. and Bunch, D. S. (1992). Heterogeneity and state dependence in household car ownership: a panel analysis using ordered-response probit models with error components, in: M. Koshi (Ed.), *Transportation and Traffic Theory*, pp. 477–496 (Amsterdam: Elsevier).

Kitamura, R., Golob, T.F., Yamamoto, T., Wu, G. (2000). Accessibility and auto use in a motorized metropolis, *Paper presented at the 79th Transportation Research Board Annual Meeting*, Washington, DC.

Kuo, L. and Chen, Z. (2004). A State Duration Model for Brand Choice and Inter-Purchase Time, *Journal of Data Science*, Vol. 2, pp. 125-147.

Kweon, Y.J. and Kockelman, K. (2004). Nonparametric regression estimation of household VMT, *Annual Meeting of the Transportation Research Record*

Kockelman, K. (1997). Travel Behavior as a Function of Accessibility, Land Use Mixing, and Land Use Balance: Evidence from the San Francisco Bay Area. *Transportation Research Record* 1607, pp. 117-125.

Koppelman F., Bhat, C.R., Sethi, V. and Williams, B. (2003). A Self-Instructing Manual on Discrete Choice Modeling, Prepared for Federal Highway Administration.

Kubarych, R.M. (2004). Impact of volatile auto sector on the U.S. economy, Council of Foreign Relations, website: http://www.cfr.org/pub7192/roger_m_kubarych/impact_of_a_volatile_auto_sector_on_the_us_economy.php

Kveiborg, O. (1999) Forecasting developments of the car fleet in the Altrans Model, *Paper presented to the Nordic Research Network on Modeling Transport, Land-Use and the Environment*, 3rd Workshop, Trondheim, Norway.

Lerman, S., and Ben-Akiva, M. (1976). A Behavioral Analysis of Automobile Ownership and Mode of Travel, Vol. 2, Technical Summary, U.S. Department of Transportation.

Leszczyc, P.P. and Bass, F.M. (1998). Determining the effects of observed and unobserved heterogeneity on consumer brand choice, *Applied Stochastic Models and Data Analysis*, 14, pp. 95-115.

Litman, T. (1995). Land use impacts costs of transportation, *World Transport Policy and Practice*, Vol. 1, No. 4, pp. 9 – 16.

Litman, T. (2002). The costs of automobile dependency and the benefits of balanced transportation, Victoria Transport Policy Institute, Canada

Litman, T. (2005). Evaluating Transportation Equity: Methods for Incorporating Distributional Impacts Into Transport Planning, Victoria Transport Policy Institute, Canada

Litman, T. and Laube, F. (2002). Automobile dependency and economic development, Victoria Transport Policy Institute, Canada

Lave, C.A. and Train, K. (1979). A disaggregate model of auto-type choice, *Transportation Research Part A*, Vol. 13, No. 1, pp. 1–9.

Louviere, J.J., Hensher D.A. and Swait, J.D. (2000). *Stated Choice Methods – Analysis and Application*, Cambridge: Cambridge University Press.

Louviere, J., Train, K., Ben-Akiva, M., Bhat, C.R., Brownstone, D., Cameron, T.A., Carson, R.T., DeShazo, J.R., Fiebig, D., Greene, W., Hensher, D. and Waldman, D. (2005). Recent Progress on Endogeneity in Choice Modeling, *Forthcoming, Marketing Letters*, Vol. 16, No. 2-3.

Madre, J.L. (1990). Long term forecasting of car ownership and use. In P. Jones (ed.), *Developments in Dynamic and Activity Based Approaches to Travel Analysis*, Oxford Studies in Transport, Gower Publishing, Aldershot, England.

Mannering, F. (1983). An Econometric Analysis of Vehicle Use in Multi-Vehicle Households, *Transportation Research Part A*, Vol. 17, No. 3, pp. 183-189.

Mannering, F. and Winston, C. (1985). A dynamic empirical analysis of household vehicle ownership and utilization, *Rand Journal of Economics*, Vol. 16, No. 2, pp. 215–236.

Mannering, F., and Mahmassani, H. (1985). Consumer Valuation of Foreign and Domestic Vehicle Attributes: Econometric Analysis and Implications for Auto Demand, *Transportation Research Part A*, Vol. 19, No. 3, pp. 243-251.

Mannering, F. (1986). A Note on Endogenous Variables in Household Vehicle Utilization Equations, *Transportation Research Part B*, Vol. 20, No. 1, pp. 1-6.

Mannering, F.L. and Winston, C. (1991). Brand Loyalty and the Decline of American Automobile Firms, *Brookings Papers on Economic Activity: Microeconomics*, pp. 67-114.

Mannering, F., Winston, C., Starkey, W. (2002). An exploratory analysis of automobile leasing by US households, *Journal of Urban Economics*, Vol. 52, No. 1, pp. 154–176.

Manski, C.F. and Sherman, L. (1980). An empirical analysis of household choice among motor vehicles, *Transportation Research Part A*, Vol. 14, No. 6, pp. 349–366.

McCarthy, P.S. (1996). Market Price and Income Elasticities of New Vehicle Demands, *Review of Economics and Statistics*, Vol. 78, No. 3, pp. 543-547.

McCarthy P.S. and Tay R.S. (1998). New Vehicle Consumption and Fuel Efficiency: A Nested Logit Approach, *Transportation Research Part E*, Vol. 34, No. 1, pp. 39-51

McFadden, D. (1973). Conditional Logit Analysis of Qualitative Choice Behavior,in P. Zarembka (ed.), *Frontiers in Econometrics*, pp. 105-142, Academic Press: New York.

McFadden, D. (1977). Modeling the choice of residential location, *Cowles Foundation Discussion Paper* No. 477.

McFadden, D. and Train, K. (2000). Mixed MNL models for discrete response, *Journal of Applied Econometrics*, Vol. 15, Issue 5, pp. 447 - 470.

Meurs, H.J. (1991). *A Panel Data Analysis of Travel Demand* (Groningen: Groningen University).

Meurs, H. (1993). A panel data switching regression model of mobility and car ownership, *Transportation Research Part A*, Vol. 27, No. 6, pp. 461–476.

Mohammadian, A., and Miller, E.J. (2003a). Dynamic Modeling of Household Automobile Transactions, in the *Journal of the Transportation Research Record*, No. 1831, pp. 98-105.

Mohammadian, A., and Miller, E.J. (2003b). Empirical Investigation of Household Vehicle Type Choice Decisions, *Journal of the Transportation Research Record*, No. 1854, pp. 99-106.

Mohammadian, A. and Miller, E.J. (2003b). An empirical investigation of household vehicle type choice decisions, *Forthcoming in Transportation Research*.

MORPACE International, Inc. (2002). *Bay Area Travel Survey Final Report*, March. ftp://ftp.abag.ca.gov/pub/mtc/planning/BATS/BATS2000/

Newman, P. and Kenworthy,J. (1998). *Sustainability and Cities: Overcoming Automobile Dependency*, Island Press.

Nobile, A., Bhat, C. and Pas, E. (1996). A Random Effects Multinomial Probit Model of Car Ownership Choice, *Research Paper* (Amherst, MA: Duke University and University of Massachusetts).

Page, M., Whelan, G. and Daly, A. (2000). Modelling the factors which influence new car purchasing, *Paper presented at the European Transport Conference*, PTRC, Cambridge, UK.

Pagliara, F and Preston, J. (2003). The impact of transport on residential location, Final Report TN6, Transport Studies Unit, University of Oxford.

Parks, R.W. (1977). Determinants of Scrapping Rates for Postwar Vintage Automobiles, *Econometrica,* Vol. 45, No. 5, pp. 1099-1115.

Petrin, A. (2002). Quantifying the Benefits of New Products: The Case of the Minivan, *Journal of Political Economy*, Vol. 110, pp. 705-729.

Pickrell, D. and Schimek, P. (1998). Trends in Personal Motor Vehicle Ownership and Use: Evidence from the Nationwide Personal Transportation Survey, U.S. DOT Volpe Center

Pucher, J. and Renne, J.L. (2003). Socioeconomics of urban travel: Evidence from 2001 NHTS, *Transportation Quarterly*, Vol. 57, No. 3, pp. 49-77.

Schipper, M.A. (2004). Supplemental data for 2001 NHTS, *Presentation at TRB 83rd annual meeting*.

Segal, L. (1999). Review of Health Costs of Road Vehicle Emissions, Centre for Health Program Evaluation, Working Paper 94

Small, K.A. (1997). Economics and urban transportation policy in the Unites States, *Regional Science and Urban Economics*, Vol. 27, pp. 671-691.

Schrank, D. and Lomax, T. (2005). The 2005 urban mobility report, Texas Transportation Institute, Texas A & M University.

TR News (2001). Critical issues in transportation in 2002, *TR News* 217, Transportation Research Board, The National Academies.

Train, K. (1980). The Potential Demand for Non-Gasoline-Powered Automobiles, *Transportation Research Part A*, Vol. 14, pp. 405-414.

Train, K. (1986). *Qualitative Choice Analysis: Theory, Econometrics, Application to Automobile Demand*, MIT Press, Cambridge, Massachusetts.

Train, K. and Winston, C. (2004). Vehicle choice behavior and the declining market of U.S. automakers, Working paper, Department of Economics, University of California, Berkeley.

Train, K. and Lohrer, M. (1982). Vehicle Ownership and Usage: An Integrated System of Disaggregate Demand Models, Cambridge Systematics, Inc., Berkeley, California.

Untermann, R. and Moudon, A.V. (1989). Street Design; Reassessing the Safety, Sociability, and Economics of Streets, University of Washington, Dept. of Urban Planning, Seattle, p. 3.

VTPI (2004). Automobile Dependency: Transportation and Land use patterns that cause high levels of automobile use and reduced transport options, TDM Encyclopedia.

Walsh, J.W. (1995). Flexibility in consumer purchasing for uncertain future tastes, *Marketing Science*, Vol. 14, pp. 148-165.

West, S. (2004). Distributional Effects of Alternative Vehicle Pollution Control Policies, forthcoming in *Journal of Public Economics*, Department of Economics, Macalester College.

Wharton Econometric Forecasting Associates. (1977). An Analysis of the Automobile Market: Modeling the Long Run Determinants of the Demand for Automobiles, Vol. 1 and 2, U.S. Department of Transportation.

Whelan, G., Wardman, M. and Daly, A. (2000). Is there a limit to car ownership growth? An exploration of household saturation levels using two novel approaches, *Paper presented at the European Transport Conference*, PTRC, Cambridge, UK.

Whelan, G. (2001). Methodological advances in modelling and forecasting car ownership in Great Britain. *Paper presented at the European Transport Conference*, PTRC, Cambridge, UK.

Yamamoto, T., Kitamura, R. and Kimura, S. (1999). A Competing Risk Duration Model of Household Vehicle Transactions, *Transportation Research Record*, No. 1676, pp.116-123.

Yamamoto, T. and Kitamura, R. (2000). An analysis of household vehicle holding durations considering intended holding durations, *Transportation Research Part A*, Vol. 34, pp. 339-351.

Vita

Sudeshna Sen was born in Patna, India on December 4, 1978. She is the daughter of Sujoy Sen and Shukla Sen. After completing her work at G. D. Birla Girls' High School, Kolkata, in 1996, she entered the Indian Institute of Technology, Kharagpur, India. In May 2001, she graduated with the degree of Bachelors in Architecture. Ms. Sen then enrolled at the University of Illinois at Chicago, in the fall of 2001 for graduate study in Transportation Planning. She received the degree of Master of Urban Planning and Policy in July 2003. In August 2003, she began her doctoral study in Transportation Engineering at the University of Texas at Austin.

Permanent address: Orbit Heights, Flat - 3C
33 South Gariahat Road
Dhakuria, Kolkata - 700031
West Bengal, India.

This dissertation was typed by the author.